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Can Wikipedia Article Traffic Statistics be Used to Verify a Technical Indicator? An Exploration into the Correlation Between Wikipedia Article Traffic Statistics and the Coppock Technical Indicator.

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Can Wikipedia Article Traffic Statistics be used to verify a Technical Indicator? An exploration into the correlation between Wikipedia Article Traffic Statistics and the Coppock Technical Indicator.

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A dissertation submitted in partial fulfilment of the requirements of

Dublin Institute of Technology for the degree of

M.Sc. in Computing (Data Analytics)

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DECLARATION

I certify that this dissertation which I now submit for examination for the award of MSc in Computing (Data Analytics), is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the test of my work.

This dissertation was prepared according to the regulations for postgraduate study of the Dublin Institute of Technology and has not been submitted in whole or part for an award in any other Institute or University.

The work reported on in this dissertation conforms to the principles and requirements of the Institute's guidelines for ethics in research.

Signed: ________________________________

Cormac O'Connor

Date: ***6th March 2015***

ABSTRACT

Recent studies have shown that, through the quantification of Wikipedia Usage Patterns as a result of information gathering, stock market moves can be predicted (Moat et al 2013). There was also research performed to determine the predictive nature of Wikipedia Data to predict movie box office success (Mestyan et al. 2013). The goal of any investor, in order to maximize the return of their investments, is to have an edge over other participants in the markets. Several tools and techniques have been used over the years to fulfil this, some proving to generate a consistent stream of income (Gillen 2012). With the improvement of technology and communication links, what was once considered a closed door, gentleman's club operation, can now be tapped into by anybody who has access to a PC and communications link.

It is said that approximately only 20% of investors are consistently successful in their investments (Terzo 2013). In order be successful, there needs to be a strategy in place that is strictly adhered to. The objective of these trading systems is to minimize, or ideally cut out, the human emotion factor and naturally, as a consequence, allow the strategy operate at its optimum. An example of this is through the use of technical analysis indicator which, when used correctly, can net the investor considerable, consistent returns. (Gillen 2012). Technical indicators, such as Coppock, are widely used in the field of stock market investment to provide traders and investors with an insight into which direction a stock or index is moving so as to facilitate the optimum time to enter or exit the market. This project investigates whether Wiki Article Traffic Statistics can be used to verify trading signals given by the Coppock technical indicator through the use of a suitable correlation technique.

Keywords: *Technical Analysis, Wikipedia, Coppock Indicator, Momentum, Correlation.*

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I would like to thank Mirko Kaempf, who through a series of discussions helped me to solidify my idea and use the Wikipedia data source as a research topic.

Thanks to my parents who were always on hand to assist at home with my three boys Cian, Neil and Rory, when I was unavailable due to the demands of the dissertation.

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1 INTRODUCTION

It is estimated that the financial crisis of 2008 cost Americans between $6 trillion and $14 trillion, which translates to $50,000 and $120,000 for every US household (Luttrell et al. 2013). This financial crisis brought to people's attention how quickly and severely one's wealth can be destroyed, and the importance of preventing this through proper money management and investment strategy. A number of large US corporations suffered, as with the collapse of Bear Stearns and Lehman Brothers, and the near collapse of Fannie Mae and Freddie Mac, the latter two requiring a bailout by the US Federal Reserve. It is the cause and consequence of these failures that added fuel to the fire of the financial downturn, and which financially affected such a large number of innocent institutions and investors.

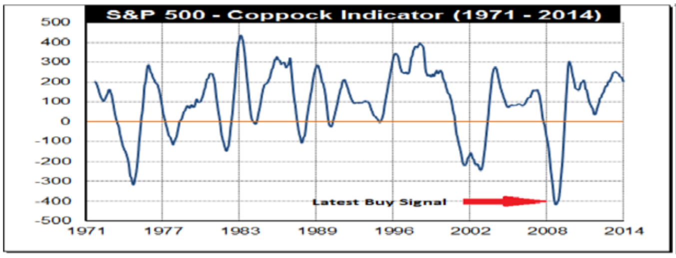
In order to prevent one's wealth from being destroyed during a downturn period, it requires the use of reliable and proven signals called technical indicators. A technical indicator is a stock analysis methodology which is used to forecast the direction of share prices and/or stock market indexes through the use of historic market data. These can be used to signal a potential downturn, and thus, through active steps by the institution or investor, can save a large amount of capital that is invested in the stock market. Equally, technical indicators can signal to an investor the optimal time to enter into the stock market and maximise any potential gains. A number of well-known technical indicators can assist investors in predicting the market direction. These include MACD (moving average convergence divergence), RSIs (relative strength indicators), the stochastic oscillator and the Coppock indicator (Gillen 2012).

Another source of information which can assist an investor is the availability of Wikipedia article traffic statistics. These statistics are openly available to the public, providing the number of page views and page edits made by the Wikipedia audience. Through the use of these statistics, it is possible to determine an interest factor concerning a particular page, and to build a history of viewership. By using the Wikipedia article traffic statistics, it may be possible to complement the signal given by some of these technical indicators, such as the Coppock indicator.

1.1 Background

The Coppock indicator was invented by Edwin “Sedge” Coppock, and first published in *Barron’s Magazine* on October 15th, 1962 (Nicholson 2010). The idea came about as a result of Coppock being approached by his local church minister concerning best investment strategies, to ensure that they had their money invested to its best potential. Coppock believed that suffering a loss as a result of a market downturn was like a bereavement, which also required a period of mourning. Therefore, Coppock, in return, asked the church minister how long it took, on average, for a person to fully mourn the death of a loved one. The estimate given was between 11 and 14 months.

Coppock concluded that, as a result of a market drop, the bereavement period would be similar to the death of a loved one, and, consequentially, the same could be applied to a loss suffered on the stock market. From this, it could be possible to predict the optimum time to re-enter the market. Simply put, it is a momentum indicator which oscillates above and below the X-axis, which, when there is a crossover from negative to positive, would indicate a time to buy into the market. Figure 1.1 demonstrates the success of the Coppock indicator on the S&P Index between 1971 and 2014. It has given 11 buy signals, and has performed well over a 1-year/3-year/5-year period. As can be understood from the figure, of the 11 Coppock signals given, only one year (2001) returned a negative return after one year but became profitable, like the other years, from Year 3 onwards.



The Coppock Indicator
Signals on S&P 500 Index Since 1970

Date	S&P 500 Level	Subsequent Returns 1 Year	3 Years	5 Years
31-Jan-75	78	29.6%	15.6%	47.9%
30-Apr-78	98	4.1%	35.9%	66.0%
31-Aug-82	118	38.9%	59.5%	173.5%
31-Dec-85	167	26.3%	47.1%	111.3%
30-Sep-88	271	29.3%	43.4%	70.0%
28-Feb-91	370	11.3%	25.4%	73.9%
31-Jan-95	470	35.7%	112.9%	199.6%
31-Dec-01	1,148	-23.4%	4.7%	23.5%
30-Nov-02	935	14.5%	33.7%	58.5%
30-Apr-03	916	22.0%	43.1%	51.3%
31-May-09	919	18.5%	39.1%	109.4%
Average Returns		**18.8%**	**41.9%**	**89.5%**

Figure 2.1: Coppock indicator performance between 1971 and 2014 (inclusive).

Despite the fact that the Coppock indicator was originally designed to work on monthly data, and to only be used to indicate a “buy” signal following a period of decline, this indicator can be used to work on more frequent data – for example, daily price data – and also to be used to give the investor a “sell” signal (Mitchell 2014). As a result of the facilitation of more frequent time periods and both buy and sell signals, the Coppock indicator can be used to further increase the potential returns to an investor.

The biggest drawback with the Coppock indicator relates to the “false” signals which occur when the Coppock value crosses above or below the X-axis, only to quickly cross back in the opposite direction immediately after. This can create confusion for the investor, who thus loses confidence in the signal’s real value and reliability. Therefore, it is important to have the parameters required for the Coppock calculation tuned relative to the frequency of data being analysed. In addition, as mentioned, Coppock originally designed the indicator to signal when the line crossed the X-axis, but some investors have refined this further, in order to increase profits, so as to enter or exit the market when there is a change in direction from a trough or peak of the Coppock time series (Mitchell 2014). Using Wikipedia page view statistics, it may be possible to verify the signal given by the Coppock indicator by using the data for each associated Wikipedia page, whether relating to a stock market index (DJIA, DAX) or individual stock contained in that associated index. Using this confirmation from the Wikipedia article traffic statistics, it may be possible to verify the signal that the Coppock indicator gives.

1.2 Research problem

The Coppock indicator has a proven track record when it is applied using its original design criteria – to provide a buy signal when applied against monthly data (Gillen 2012). For example, on the S&P Index since 1975, there have been 11 buy signals provided by the Coppock indicator. Only one of these signals, in the year 2001, proved to be incorrect. Therefore, it can be understood that the Coppock indicator is a very reliable indicator for the long-term investor when used against monthly data. This is not very useful, however, in the midst of a financial crisis or any short-term event, as the damage to one’s wealth will have passed before any suitable signal is given. Therefore, in order to improve on this, a more detailed analysis is required on the data given. To facilitate this tighter window, the Coppock signal can also be derived from daily data.

Because the Coppock indicator is a Smoothed momentum oscillator, where the rate-of-change measures momentum and the weighted moving average performs the smoothening of the data, the indicator can be run against any time frame. In order to optimise the financial returns through the use of the Coppock indicator over shorter time frames (daily in this case), the parameters for calculation may need to be adjusted to reflect this. Shorter rates-of-change will result in the Coppock curve becoming faster and more sensitive, while longer settings will make it less sensitive.

A method of confirming the signal given by the Coppock curve through the use of Wikipedia article traffic statistics may result in a better-performing investor fund by yielding the investor higher returns.

1.3 Research aim and objectives

The main aim of this dissertation is to determine whether the signal given by the Coppock indicator can be confirmed through the use of associated Wikipedia article traffic statistics.

As a consequence, an investor may be able to make better trading decisions through the Coppock indicator, in conjunction with the confirmation achieved through the associated Wikipedia signal. The correlation achieved between the Wikipedia article traffic statistics and Coppock values will verify whether there is value in using the Wikipedia article view statistics as a verifying indicator.

The main objectives of this dissertation are as follows:

1. To determine correlations between different datasets: Research was conducted concerning the Coppock indicator, its characteristics and its performance over different time ranges. A review of existing techniques used to determine correlations between different datasets was performed.
2. To test whether Wikipedia article traffic statistics verified the existing Coppock indicator: An experiment was designed to test this. This was achieved by testing correlations between Wikipedia article traffic statistics for two stock

market indexes (Dow Jones, German DAX) and five stocks contained in each index against associated Wikipedia article traffic statistics for each page on that stock or index.

3. To confirm whether there is value in using Wikipedia article view statistics: An analysis was performed on the results obtained from each index and stock to confirm this. An exercise was used to determine what time series correlation method worked best, along with a range of different parameters used in the generation of the Coppock signal (rate of change, weighted moving average). This would determine the success or failure of the experiment, based on the results obtained.
4. To identify future areas of research which may improve and assist in determining a better correlation between both data sets.

1.4 Research methodology

i. Objective 1 has been achieved through a literature review of the Coppock indicator and the uses of it over different frames other than the monthly time frame for which it was originally designed. Information concerning the different correlation techniques was also gained through the literature review.
ii. Objective 2 has been achieved through the detailed design of experiments, in order to determine whether there is a correlation between the two datasets. This has been achieved by the use of suitable normality tests and the appropriate correlation checks performed thereafter.
iii. Objective 3 has been achieved through the execution and gathering of correlations determined through the research methodology. These results are evaluated in order to determine the relationship between the two datasets.

1.5 Scope and limitations

Stock market price data and associated Wikipedia article traffic statistic data for two stock markets were selected: the German DAX exchange and the US Dow Jones Industrial Average (DJIA) exchange. Five of the largest capitalised stocks were chosen from each associated index. Two years were chosen for analysis: 2008 and 2014. Because the Wikipedia datasets contained all traffic for every page on an hourly basis, it was not feasible to download these for each year in order to extract the selected

Wikipedia page traffic. The alternative was to download Wikipedia traffic data through the manual JSON download facility, and subsequently extract data for each stock and year/month in question. In a real-world environment, there would be sufficient space to download a full dataset and perform an analysis on every stock belonging to each stock market index.

1.6 Organisation of dissertation

The dissertation is organised as follows:

> **Chapter Two** will cover research conducted in the area of technical analysis, and will then focus specifically on the Coppock indicator, how it is derived and steps taken to improve its performance depending on the frequency of data to which it is applied. Following this, research completed using Wikipedia article traffic statistics in the area of stock market investments, and how it has been used to better improve returns on investment for the investor, will be addressed. It will also cover research conducted in regard to correlations between similar datasets, and how best to use these.
>
> **Chapter Three** will concentrate on the experiment, its design and the implementation of the model. It will detail the collection of data, its structure and evaluation methods for the models. Any data cleaning and transformation that is required in order to make the data as effective as possible will be outlined. Finally, a detail of the correlation methodologies used will be presented, with the results of this discussed.
>
> **Chapter Four** will focus on the implementation and evaluation of the experiment, and how the datasets were correlated to determine whether there is value in including Wikipedia article traffic statistics in order verify the signal given by the Coppock indicator. This chapter will also cover the issues around missing weekend/bank holiday data, and how this was addressed in order to correlate with the Wikipedia article traffic statistics dataset. The evaluation done in order to determine the effectiveness of the Wikipedia data when added

to the Coppock indicator will be outlined. A number of time periods within the years 2008 and 2014 will be analysed along with various parameter changes to the Coppock signal and Wikipedia data, to determine the optimal correlation.

Chapter Five will report on the results from the implementation and experiments, as outlined in Chapter 4. These results will be analysed and compared to the findings derived from the literature review.

Chapter Six will conclude the dissertation and provide an overview of the work carried out during the course of the experiment. Further areas of investigation and research will be highlighted in order to potentially improve on the results found.

2. LITERATURE REVIEW

A vast amount of work has been completed in determining methods of defining new technical indicators or in the refinement of existing indicators in order to improve the return on one's investment. This continues to be done by both large institutions and private investors alike. Timing in regard to when to enter and exit a trading position on the stock market has been the quest of investors over the years. As a result, several techniques have been created to assist traders and investors on when to time the entry and exit on the market most effectively. Some of these techniques include the 30/50 day moving average strategy, the Dow Theory and the Coppock indicator (Gillen 2012).

In a situation where buyers outnumber sellers, the market moves upwards; when sellers outnumber buyers, the market moves downwards. Each buyer and seller is acting on a belief that his/her decision is correct and appropriate relative to what is occurring in the market at that point in time. Therefore, it is safe to claim that everyone's view is priced into the market, and is thus representative of the market condition at that time (Elder 1993). In the investment book *The Intelligent Investor* (Graham 2005), it was determined that there were two key approaches to successful investing on the stock market. The first is through the identification of stocks that were priced below their intrinsic value, called value investing. The second approach is through the timing of the stock market. This popular approach used to time the stock market and its associated moves is achieved through a technique called technical analysis.

2.1 What is technical analysis?

Professionals in the stock market are constantly attempting to time the market so that they can maximise their profits through the strategic closure of open positions before a drop in the stock markets occurs (bear market) and/or an opening of new positions in the market occurs again before an established upturn (bull market). According to Pring (2002), a specific definition of technical analysis can be presented as follows: "The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.”

Large revenues are made by training companies which, in many cases, charge high fees offering the “silver bullet” to time the market perfectly, and which also offer the purchaser maximum profits with minimum risk (Kemp 2014). Such an approach is difficult to achieve, as it requires a great deal of study, practice and patience. However, through sufficient study of technical analysis and the respectful use of the associated indicators that exist, an investor can achieve consistent returns over the long term. Therefore, the “noise” that exists through the news and media, of which 90% is of no value to the investor (Gillen 2012), can be ignored by the investor, and more attention spent on what the technical indicators are reporting.

Technical analysts use charts to study market action, with the objective of uncovering recurring market action. The basis of any chart used to perform technical analysis requires the following values for each day (Elder 1993):

- Opening price: This is generally the opinion of the amateur who has digested the news from the previous day, and has requested a trade to be placed at the opening of the market.
- Closing price: This is the price which the professionals consider to be the true value of the share. Generally, they monitor the behaviour of the amateurs, and become active as the close of market approaches.
- Daily high: This reflects the battle between the bulls and bears on that day. In this case, it reveals the strength of the bulls on the day.
- Daily low: Similarly to the daily high, this reveals the battle between the bears and the bulls, revealing the strength of the bears on the day.

The goal of a technical analyst is to identify patterns that exist when a set of daily data is produced on a chart, and to profit from the anticipated movement that can be predicted from these trends. As can be seen in Fig. 2.1 (stockcharts.com), each day is represented by a candlestick, where the direction of the day is indicated by the colour (red: decrease in stock value; green: increase in stock value). In its simplest form, the technical analyst will also use some overlay indicators to assist in determining the strength of direction of the underlying share or index.

Figure 2.1: Simple technical chart of the DAX Index, featuring candlesticks and moving averages.

Moving averages (MAs) are commonly used which indicate to the analyst where the strength in direction is. The longer the time frame of the moving average line, the slower it will react to daily market prices. Conversely, the shorter the time frame on which the moving average line is based, the faster it will react to any daily price movement. As highlighted by Allen and Karjalainen (1998), a common investment strategy using the moving averages is one where a “buy” signal is given when the 30-day MA crosses above the 50-day MA. This signal is strengthened when the 50-day MA has an upward trend. A “sell” signal is given when the 30-day MA crosses below the 50-day MA. On top of this, the “sell” signal is strengthened when the 50-day MA has a downward trend. As recommended by Shipman (2008), the use of the moving average approach helps to remove short-term volatility apparent in the underlying market, thereby assisting traders in detecting the trend, and any investment opportunity that may appear.

A popular set of technical indicators used to determine the strength and direction of a share or market are known as momentum indicators (Gillen 2012).

Momentum is defined as the difference between the current closing price and the closing price n days ago, determined by the trader/investor.

$$momentum = close_{today} - close_{N\ days\ ago}$$

Therefore, if the current price is higher than the earlier price, it is said to have a positive momentum. The opposite occurs when the current price is less than the earlier price, returning a negative momentum. A simple trading strategy can be applied using a combination of price momentum, where, if combinations of derived momentums cross from negative to positive, a "buy" signal is generated. The opposite occurs when the momentum line crosses from positive to negative, thus returning a "sell" signal, as is demonstrated in Figure 2.2. Bird and Casavecchia (2005) in their study of investment improvement through the use of momentum indicators found that there was an increase in investment returns through the use of price momentum.

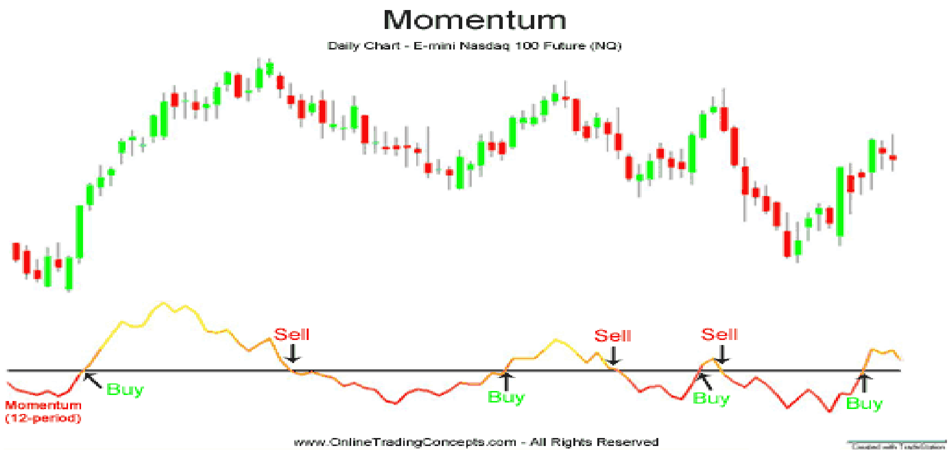


Figure 2.2: Using momentum signals as a method of entering/exiting (buy/sell) a market position.

Another related indicator is called the rate of change (ROC), which scales the momentum value by the old close price, thus becoming a fraction.

$$rate\ of\ change = \frac{close_{today} - close_{N\ days\ ago}}{close_{N\ days\ ago}}$$

If there is a consistent set of positive momentum values, this indicates that there is an uptrend in place. Conversely, if there is a consistent set of negative momentum values, this indicates that there is a downtrend in place. Therefore, if the ROC trend line crosses the x-axis from negative to positive, this signals a buying opportunity, while, if the trend line crosses the x-axis from positive to negative, this signals a selling opportunity. Momentum and ROC are often used to determine the best time to enter or exit the market.

Technical indicators, therefore, offer investors a strategic method of investing through the use of historic data in order to best predict which direction a market will take over the time frame on which the trader/investor is focused. They have been used by a wide audience of investors, some of which have been successful in their predictions, others not so successful. Therefore, it is important to choose a technical indicator, or a number of indicators, that have a proven track record, which work well for that trader, and which the trader has proven to operate successfully over the long term. This is normally achieved through trial and error; thus, it advised that a demo account be used, where fictitious money is used to trade the stock market and prove whether a given trading strategy using certain technical indicators yields a profitable result. Technical indicators are used on short-, medium- and long-term time ranges, and are adopted by short-term, speculative traders and long-term investors.

2.2 The Coppock indicator

A reliable performance momentum technical indicator is the Coppock indicator. According to Gillen (2012), when used against monthly data on the US S&P 500 Index, the Coppock indicator has given 11 “buy” signals since 1970. Ten out of the 11 signals yielded a positive return after one year of being signalled and more substantial returns over a longer period. For example, three years after the initial “buy” signal, the average return amounted to 42% and 88% after five years. Therefore, all factors combined would indicate that the Coppock indicator is a reliable tool which yields a respectable return to the investor.

The Coppock Indicator				
Signals on S&P 500 Index Since 1970				
	S&P 500	Subsequent Returns		
Date	Level	1 Year	3 Years	5 Years
31-Jan-75	78	29.6%	15.6%	47.9%
30-Apr-78	98	4.1%	35.9%	66.0%
31-Aug-82	118	38.9%	59.5%	173.5%
31-Dec-85	167	26.3%	47.1%	111.3%
30-Sep-88	271	29.3%	43.4%	70.0%
28-Feb-91	370	11.3%	25.4%	73.9%
31-Jan-95	470	35.7%	112.9%	199.6%
31-Dec-01	1,148	-23.4%	4.7%	23.5%
30-Nov-02	935	14.5%	33.7%	58.5%
30-Apr-03	916	22.0%	43.1%	51.3%
31-May-09	919	18.5%	39.1%	109.4%
Average Returns		**18.8%**	**41.9%**	**89.5%**

Table 2.1: The Coppock indicator: track record of "buy" signals on S&P Index since 1970.

The indicator is derived by calculating the weighted moving average (WMA) of the rate of change (ROC) of a market index. A weighted moving average assigns a higher weighting to more current data points, as they are more relevant than the data points in the past (Elder 1993).

$$\text{WMA}_M = \frac{np_M + (n-1)p_{M-1} + \cdots + 2p_{(M-n+2)} + p_{(M-n+1)}}{n + (n-1) + \cdots + 2 + 1}$$

Therefore, the Coppock indicator is calculated by adding both rates of change (11 months and 14 months, respectfully) together and performing a weighted moving average (10 month) on the result.

$$Coppock = WMA[10]\ of\ (ROC[14] + ROC[11])$$

Following the original invention of the Coppock indicator, it has since been customised by more short-term, speculative traders to work over more frequent time frames (i.e. weekly, daily, etc.). Furthermore, it is also used by traders to signal a "selling" opportunity, and thus facilitates both the entry and exit of a trade entered on the stock market. Dependant on the level of risk tolerance the investor possesses, the sensitivity of the Coppock indicator can be tuned through the adjustment of the ROC and WMA parameters applied. By decreasing the WMA, this causes the result to signal an entry or exit stock market position slightly earlier. Increasing the WMA causes the result to signal slightly later for both entry and exit positions.

The Coppock curve can be acted upon in two different ways. Coppock originally designed the curve to signal a buy signal only, when the line crossed from positive to negative, and returned back to positive. Coppock anticipated that, when the line crossed from negative to positive, the "buy" signal would fire. This is shown as the green vertical line in Figure 2.3. This rule has since been customised by traders to fire a "sell" signal when the line crosses from positive to negative. This sell signal is shown as the red vertical line in Figure 2.3. Many traders feel that the X axis crossover is not as reactive to the cycle change as desired, and thus fires a signal when there is a turn in the Coppock curve. An example of such a more reactive "buy" signal is given by the "buy" arrow in Figure 2.3.

Figure 2.3: Coppock signals for monthly data.[1]

[1] "Investopedia (2014) *Using the Coppock Curve to Generate Stock Trade Signals* [Online]. Available: http://www.investopedia.com/articles/active-trading/031814/using-coppock-curve-generate-stock-trade-signals.aspl [Accessed 29 November 2014]."

The advantage of entering at the turning point (buy arrow), and not at the x-axis crossover, means that the position is placed at an earlier time than waiting for the confirmation x-axis crossover. This means that there is a better chance of making a larger profit, due to the reduction of that time-loss. The disadvantage of this is that it can result in a false signal where the initial downturn occurred but was followed by a resumption upward, thus erasing any initial profit made, and resulting in a potential overall loss. Other, shorter-term strategists (Mitchell 2014) act on the signal given by the Coppock Indicator when the Coppock value has dropped from a positive value (above the X-axis) to a negative value (below the X-axis), and signals “buy” when it has turned back upward, crossing the X-axis again. This is more suited to a tighter trading frequency (hourly, daily), when false signals could be given merely by adopting the upward turn from the bottom of a negative position. Because signals will be more abundant in tighter frequencies, it is more appropriate, in these cases, to wait until the line has crossed either above (buy signal) or below (sell signal) the X-axis.

Figure 2.4: Coppock signal on daily data (signalled on zero line cross).[2]

[2] “Investopedia (2014) *Using the Coppock Curve to Generate Stock Trade Signals* [Online]. Available: http://www.investopedia.com/articles/active-trading/031814/using-coppock-curve-generate-stock-trade-signals.asp?rp=i [Accessed 29 November 2014].”

As can be seen in Figure 2.4, there are more frequent signals given on the daily chart than on the monthly chart. Therefore, depending on the frequency of data, the indicator calculation parameters (WMA and ROC) can be adjusted to result in the Coppock indicator working more optimally with the data. This can be achieved as follows (Mitchell 2014):

- Decreasing the ROC will increase the speed of fluctuations, and thus increase the number of trade signals.
- Increasing the ROC will slow the fluctuations, and therefore produce fewer signals.
- Decreasing the WMA to receive earlier entry and exit signals.
- Increasing the WMA to receive later entry and exit signals. Some traders prefer this, in order to obtain confirmation that the momentum is maintained in the same direction.
- Traders use a longer-term trend to confirm the direction of the market before placing a position using the shorter-term trends.

Therefore, two further derivations of the Coppock values can be created using parameters recommended by Mitchell (2014) and StockCharts.com (2015):-

Set 1

- 14-day Rate of Change (ROC)
- 11-day Rate of Change (ROC)
- 6-day Weighted Moving Average (WMA)

Set 2

- 20-day Rate of Change (ROC)
- 10-day Rate of Change (ROC)
- 10-day Weighted Moving Average (WMA)

These parameter sets are more suited to daily data as the Coppock signals are given a little bit earlier thus facilitating the potential to make a better return of investment.

2.3 Wikipedia article view statistics

The advent of the Web 2.0 and social networks have enabled the proposal of recommendation and reputation models for the assessment of trust of online entities (Dondio and Longo 2014; Longo et al. 2007) and the design of web-based systems (Longo et al. 2012). Similarly, the nature of social information exchange has encouraged the gathering of activity statistics by website hosts complemented the original method of exchanging information and enabling social search (Longo et al. 2009; Longo et al. 2010).

Several sources of such underlying statistical information are open to the public for downloading and analysis, including Twitter, Google Trends and Wikipedia. With the development of open access to this activity data, using proper analytical techniques, it is possible to use this information to assist in predicting what will most likely happen in the future. In Figure 2.5 and 2.6, an example is given on the Wikipedia page for the DAX Stockmarket Index and its associated Article Traffic Statistics. From this, a profile of the frequency of page views can be determined.

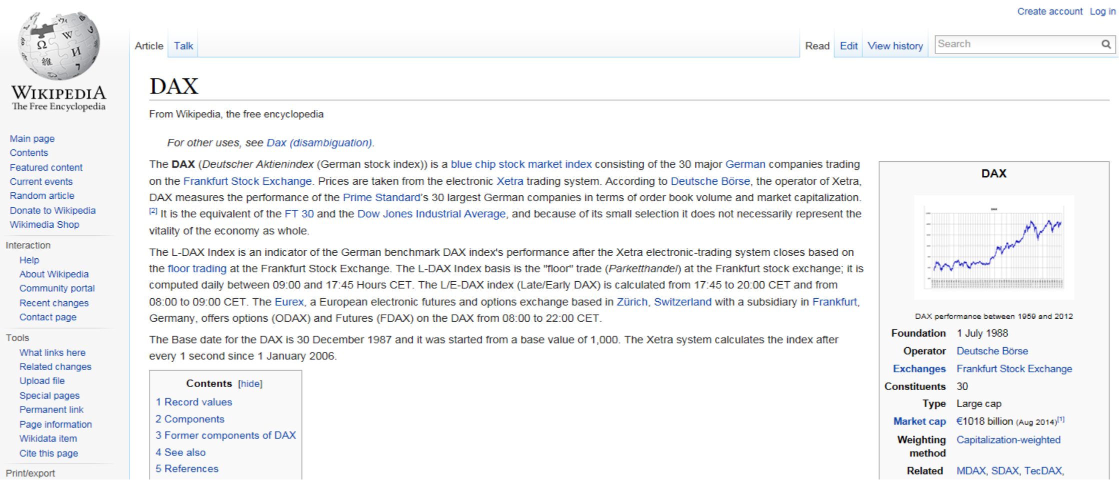


Figure 2.5: Example of Wikipedia Page containing information on the German DAX Index.[3]

[3] "Wikipedia (2014) Wikipedia GUI [Online]. Available: http://www.wikipedia.org [Accessed 29 November 2014]."

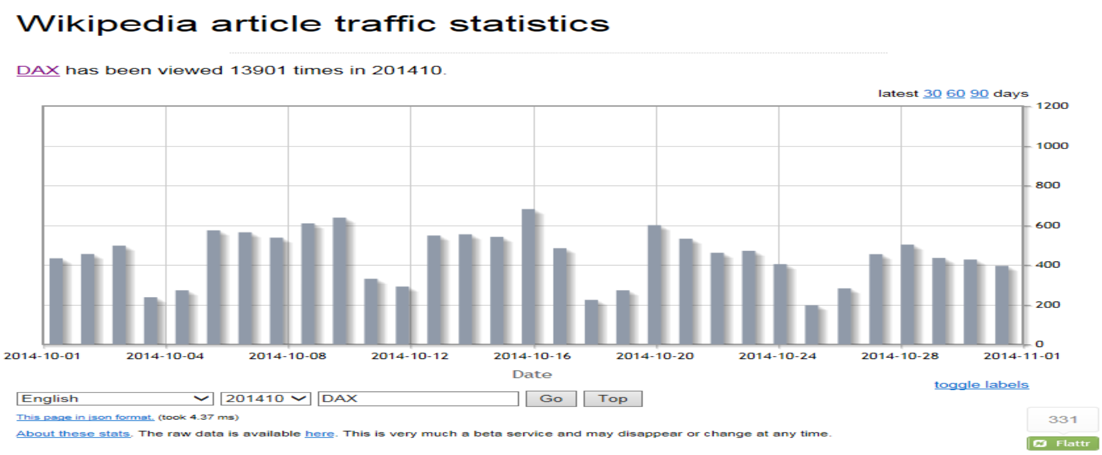


Figure 2.6: Example of Wikipedia Article Traffic Statistics on the German DAX Index.[4]

A study conducted by Preis et al. (2012) discovered that there is a relationship between the economic success of a country, using gross domestic product (GDP), and the behaviour of information searching among that country's citizens. In this study, they found that, the more prosperous a country was, based on its GDP, there was a higher likelihood of searches focusing more on the future than the past, and vice versa. Further work by Preis et al. (2013) showed that there was an increase in searches using Google Trends relating to financial markets shortly before stock markets fell on certain occasions. Preis et al. (2013) built on the Simons (1955) idea that market participants begin their decision-making process by attempting to gather information. Therefore, they concluded that financial data sets reflect the final outcome of a trader's decision-making process, regarding the decision to buy or sell a particular stock. As a result, the volume of searches for words related to financial markets could be used to produce a profitable trading strategy.

Sakaki et al. (2010) developed an alert system which, through the use of semantic analysis, used messages posted on Twitter to detect earthquakes almost in real-time. The work was to highlight that the alert system could warn at a rate faster than the event itself and thus could help reduce to the damage incurred by these events. Google Trends provides information about the information people are seeking, while Wikipedia Statistics provides insights into what information Internet users actually use

[4] "Wikipedia (2014) Wikipedia Article Traffic Statistics [Online]. Available: http://stats.grok.se/en/201410/DAX [Accessed 29 November 2014]."

(Kampf et al. 2014). Bollen et al. (2010) proved that it was possible to predict the movement of a stock market using Twitter data, with an accuracy of up to 86.9%. This was determined through the use of specific words to determine this change in sentiment. Interestingly, it was discovered that neutral words such as “calm” provided the best predictive value. This would reinforce their argument that the use of non-sentiment-related data could yield a positive result as a predictive indicator. Kamvar and Harris (2011) developed a method of continuously searching through all blogs contained on the web every 10 minutes and extracting any sentence containing the words “I am feeling” or “I feel”. From this, they were able to create a data visualisation of the mood of the world, and to categorise this into different components; for example, “Guiltiest Cities”, “Greatest Cities”, “Happiest States”, etc.

Dondio (2012) discovered that the best stock market performance is achieved when information regarding stock capitalisation is coupled with medium- and long-term web traffic. The findings revealed that both web traffic and price-related features outperform a price-only classifier, while a web-traffic-only classifier outperforms all other classifiers in predicting price increases. Therefore, it is fair to conclude that the addition of web traffic data has a positive impact on the level of predictability around a share price or index. Moet et al. (2013) analysed changes in Google query volumes for search terms related to finance, and uncovered patterns of early warning signs relating to stock market moves. They discovered that there was an increase in information gathering when there are trends to sell on the financial market at lower prices. They found that Google Trends data not only reflected the current state of the stock market, but also that this data could be used to determine certain future trends. Moat et al. (2013) continued to show that there was an increase in Wikipedia usage on particular pages related to companies and other financial topics before a stock market move, particularly a stock market fall. Due to the open availability of information and data on the Internet, websites such as Wikipedia are becoming the first point of reference when information is required. A hypothetical investment strategy was created to trade on the Dow Jones Industrial Average, where, if the average number of views for week n is greater than the previous week, the position is sold. As part of this research, they found that there was a significantly smaller number of Wikipedia page edits relative to the Wikipedia page views, therefore having little overall impact. As a consequence, they concentrated on the Wikipedia article views, and discarded the use of Wikipedia page edit data. Their evidence suggests that there is an increase in the number of page views of companies and other financial topics before stock market moves. From this, they were able to suggest that online data may allow new insights into the early stages of information gathering, to assist in decision-making.

Tversky and Kahneman (1991) present a reference-dependent theory of consumer choice, where they conclude that losses and disadvantage have a greater impact on decision than gains and advantage. Therefore, Moat et al. (2013) used these findings to conclude that more effort is devoted to information gathering on Wikipedia, as part of the early stages of the decision-making process, preceding a fall in stock market prices. It was also highlighted that people are more loss-averse, in that they are more concerned about losing £5 than about missing an opportunity to make £5.

Wikipedia is able to provide accurate, hour-by-hour article view statistics concerning activity on Wikipedia for that period. This popular Wikipedia website maintains a logging mechanism called Wikipedia article traffic statistics (WATS), created by Mituzas (2007), which records the number of times every Wikipedia page has been viewed and edited. The article traffic counter has existed since December 10th, 2007, and this information is saved in a separate compressed file on an hourly basis, which is available to download for free via a dedicated website, Wikipedia Article Traffic Statistics.[5]

The English version of Wikipedia has become the seventh most popular website globally, and the sixth most popular in the United States of America[6], recording almost 20 million views for all languages in the month of December, 2014 alone[7], of which 9.5 million views relate to the English language alone. Due to the increase in access and usage, a great deal of potential insight can be obtained from the underlying article

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[5] "stats.grok.se (2014) Wikipedia Article Traffic Statistics [Online]. Available: http://stats.grok.se/ [Accessed 29 November 2014]."

[6] "Wikipedia Popularity (2014) Audience Geography [Online]. Available: http://www.alexa.com/siteinfo/en.wikipedia.org/wiki/Main_Page [Accessed 7 January 2015]."

[7] "Page Views for Wikipedia (2015) [Online]. Available: http://stats.wikimedia.org/EN/TablesPageViewsMonthlyOriginalCombined.htm [Accessed 7 January 2015]."

view data. Since the inception of Wikipedia in 2001, it has grown in popularity, as has the number of articles available for viewing[8].

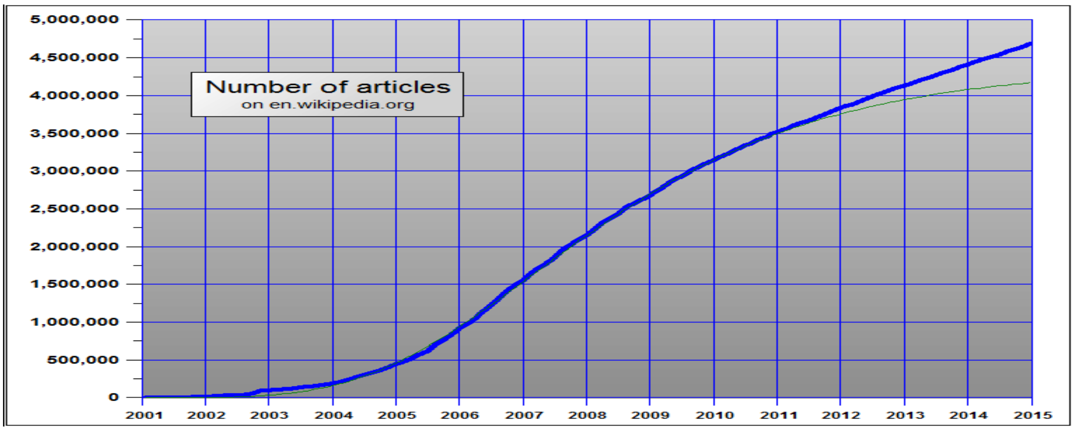

Figure 2.7: History of number of English Articles on Wikipedia.[9]

Many users prefer to visit specific pages on Wikipedia, due to the fact that it is not a means of promotion and advertising[10]. These rules concerning hosting consist of refraining from performing the following:

- Advocacy, propaganda or recruitment
- Opinion pieces
- Scandal mongering
- Self-promotion
- Advertising, marketing or public relations

Wikipedia article traffic statistics offers the following advantages:

- The data is stored on an hourly basis, while Google Trends usage is on a per-week basis. This allows for a more granular analysis of the data, thus giving the potential of more insight through the usage statistics.
- Access to data on Wikipedia has been freely available since 2007, while

[8] "Wikipedia Number of Articles - Graph [Online]. Available: http://en.wikipedia.org/wiki/File:EnwikipediaArt.PNG [Accessed 8 January 2015]."
[9] "en.wikipedia.org (2015) Wikipedia Number of Articles [Online]. Available: http://en.wikipedia.org/wiki/File:EnwikipediaArt.PNG [Accessed 14 January 14 2015]."
[10] "Funding Wikipedia through advertisements [Online]. Available: http://en.wikipedia.org/wiki/Wikipedia:Funding_Wikipedia_through_advertisements [Accessed 15 January 2015]."

Google Trends restricts the number of words that can be accessed.

- Due to the open availability of Wikipedia, data is freely accessible, unlike the limitation of Google Trends.

Some research conducted to date has used Wikipedia article view statistics. Early prediction of movie box office success was performed by Mestyan et al. (2013), through the analysis of the editing and viewing of Wikipedia information concerning the movie in question. Using linear regression modelling, they used the Wikipedia editing and viewing activities concerning 312 movies to predict the first weekend box office revenue. Because many of the Wikipedia pages were created well in advance of the movie launch, they were able to follow the popularity of these movies as that movie launch day approached. The following activity measures were used:

i. Number of views of the Wikipedia article page.
ii. Number of human editors who contributed to the page.
iii. Number of edits performed on the specific page.
iv. Collaborative rigour of the editing trail for the specific article.

It was discovered that their model was more accurate when the movie was more popular, and when the volume of the related Wikipedia article view data was large.

Alanyali et al. (2013), in their research conducted to quantify the relationship between financial news and the stock market, discovered that, when there is a greater number of mentions in the news on a given morning, it corresponded to a greater volume of trading for that company during that given day. They also discovered that there was a greater change in price for that company's stock. Their analysis also provided no evidence of a relationship between the number of mentions of a company in the morning news and the change in that company's share price when the direction of price change is considered.

Surowiecki (2004) indicates in his book *The Wisdom of Crowds* that one of humanity' greatest assets is its unrecognised ability to make accurate collective decisions, as long as each individual is not influenced by the decision of others and has made the decision based on his/her own free will. The crowd, ideally, should consist of a broad spectrum of people, from experts to novices, in the area of study. Surowiecki uses an early example from the 1900s, where, during an experiment in ox-breeding, 787 people were asked to guess the weight of an ox after it had been slaughtered and dressed. Each individual guess was incorrect, but the average of all the guesses (1197 lbs) was extremely close to the actual weight of 1198lbs. He concludes that, through the following of crowd behaviour, stock market and property bubbles are created, but, when each individual decision is made independently, there is astonishing accuracy achieved, and, when values are questioned, the results are also accurate. In a BBC Documentary, “The Code”, presented by Marcus du Sauto (2011), the wisdom of the crowd is demonstrated through an experiment which requires people to estimate the number of jelly beans contained in a glass jar (4,510 in total). Through this experiment, where each individual was not influenced by another, a guess was made by each person, and recorded. Following the gathering of guesses, all of these were totalled and averaged. Amazingly, an average of 4,515 was returned, thus proving the wisdom of the crowd theory. As many people overestimated as underestimated the number. A small number of people were very close to the correct number, while a number were very inaccurate. The key here is that, the higher the number of participants, the more likely it is that errors are cancelled out, thus revealing a very accurate estimate of the true amount.

Sanger (2009) observes that “Wikipedia is a global project. Its special feature is that no one is privileged, and over time, the views of thousands of people are weighed and mixed in. Such an open, welcoming, unfettered institution has a better claim than any other to represent the consensus of Humanity”. Similarly, there is potential crowd-behaviour value from the number of page views on Wikipedia. Kampf et al. (2012) have discovered that Wikipedia page access is mainly driven by exogenous events or by gradual shifts in public interest. This, combined with the wisdom of the crowd, could reinforce the suggestion that Wikipedia article statistics could be used to confirm or reject the signal given by the Coppock indicator.

Moat et al. (2013) remark that stock market prices capture the mood of the market at that point in time, but it is not possible to obtain a breakdown of what caused the price to arrive at the value it has. In their study, due to the availability of social data online, it was possible to obtain the information gathering that occurred before the stock market moved. Wikipedia is one of the sources of information where it is possible to build a profile of who was viewing what information at various times. Their work has uncovered methods of using Wikipedia usage patterns in advance of stock market moves, thus giving an advance warning of when this will most likely occur. By analysing the two levels of activity (page views and page edits), a comparison is made between the changes in views and edits against stock market movement over the same period, and it is concluded that Wikipedia statistics can be used as a predictor of stock market moves. It is also highlighted that investors have a tendency to search for more information about a stock or market before deciding to buy or sell a stock or share. It is noted that noticeable drops in stock markets are preceded by duration of investor concern. This concern incentivises the need to research the stock or market to which the investor is exposed. As a result, there is an increase in information gathering on that stock or index.

In order to obtain the best signal from noisy data such as Wikipedia article view statistics, a technique introduced by Schutzman (1991), which overcomes the major flaw of ROC, is the Smoothed rate of change (SROC). Each data value is responded to only once, rather than twice, where the SROC compares the values of an EMA instead of values at two points in time. This results in fewer false signals, and in the indicator signalling only once. Therefore, due to the volatility in the Wikipedia article view statistics, there is no reason to suggest that the same SROC approach cannot be applied to that set of data, thus yielding more definite signals from the dataset. The SROC is calculated as follows:

$$\text{SROC} = (\text{Current EMA} - \text{Previous EMA}) / (\text{Previous EMA}) \times 100$$

The use of the EMA, rather than the actual Wikipedia value, removes the erratic tendencies of the original ROC, thus providing a cleaner, more definite momentum indicator. This will result in a transformed data set that is more in line with the Coppock indicator dataset.

2.4 Suitable correlation techniques

Before determining the correlations that may exist between two datasets, it is important to ensure that the data is as clean as possible. Often, in cases of large datasets, there can be an occurrence of missing data due to various reasons, such as hardware or software failure, sabotage or flawed source data retrieval methods. These gaps in data can be rectified in several ways; for example, by using the last available value and filling it into the remaining missing areas. This is not ideal, especially if there is a large range of days to facilitate. Another method of filling missing data is through the use of the Holt-Winters forecasting method (Chatfield and Yar 1988). This uses a technique called triple exponential smoothening, which was introduced by Holt's student, Winters, in 1960 (Winters 1960). As long as the data is seasonal, the Holt-Winters technique can perform suitable forecasting to determine the missing value. Because the Wikipedia article traffic data generally is of a weekly, seasonal nature, by using the existing data up to the missing period, it is possible to obtain a representation of the data over the missing period in question. Figure 2.8 gives an example of Wikipedia article traffic data over a period of time. By using the seasonal nature of the data, the Holt-Winters forecasting model can provide an estimate (in blue below) as to how the data would most likely be represented.

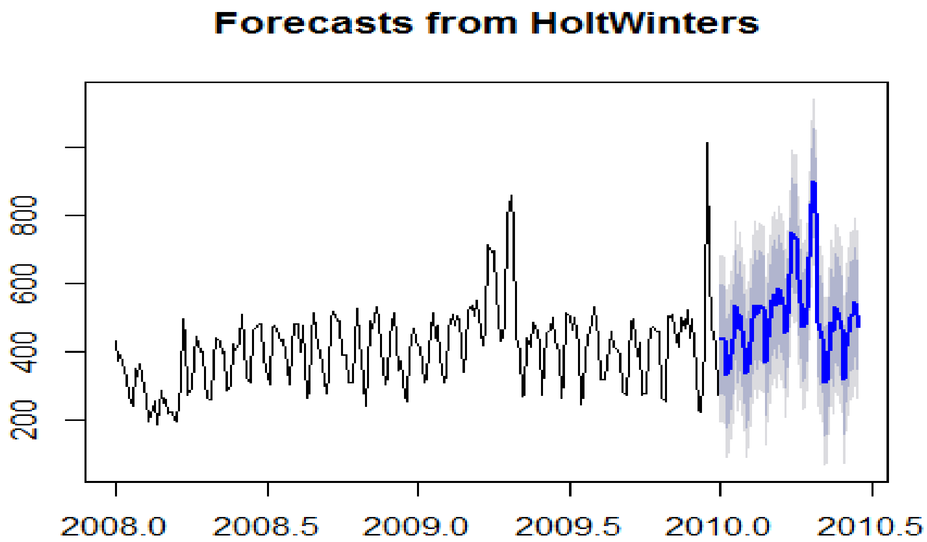

Figure 2.8: Example of Holt-Winters forecasting technique (forecast in blue – 2010.0 onwards).

Several techniques have been used to determine the correlation between financial market data and other independent sources of data. In order to determine the most suitable correlation technique between two sets of data, a test for normality is recommended. Shapiro et al. (1968) have performed statistical procedures using the following:-

W (Shapiro and Wilk, 1965) (standard third moment), b 2 (standard fourth moment), KS (Kolmogorov-Smirnov), CM (Cramer-Von Mises), WCM (weighted CM), D (modified KS), CS (chi-squared) and u (Studentized range).

This revealed that the W statistic provides the superior test for non-normality of data, and would thus be the most appropriate to use in order to determine non-normality. Non-normality is determined if the p-value is below the threshold (alpha) set. Therefore, if the p-value is below the alpha, the null hypothesis is rejected, and it is concluded that the data is not from a normally distributed population. From this, it is possible to determine the most appropriate correlation checks on the data. Some popular correlation checks performed are Pearson's; Spearman's and Kendall's techniques (Chok 2010):

1) Pearson correlation

   Mestyan et al. (2013) use Pearson correlation when performing checks to determine movie box office success using Wikipedia activity data. In order to determine the suitability of Pearson correlation, the following four criteria must be met[11].

   i. The two variables must be measured at the continuous level.
   ii. There must be a linear relationship between the two variables.
   iii. There should be no significant outliers.
   iv. Variables must be approximately normally distributed.

[11] "Pearson Product-Moment Correlation. [Online]. Available: https://statistics.laerd.com/statistical-guides/pearson-correlation-coefficient-statistical-guide.php [Accessed 23 Sept 2014]."

2) Spearman rank correlation

A Spearman rank correlation of article ratings from external rates and Wikipedia community assessment was performed by Kraut et al. (2008), and was deemed significant (r=0.54, p <0.001). Alanyali et al. (2013), when quantifying the relationship between financial news and the stock market, used the Spearman rank to determine that the daily mention of "Bank of America" corresponds to a greater daily transaction volume on the stock market for Bank of America stocks (p=0.43, $p < 0.001$). Because Spearman's correlation is computed on ranks, it depicts monotonic relationships. Should the normality test (Shapiro-Wilks) reject the null hypothesis and consider the data set non-Gaussian, the Spearman rank correlation can be used to determine the existence of any correlation between the variables. In order to use the Spearman rank correlation, the following criteria must be met:

i. Variables need to be ordinal, interval or ratio-based.
ii. The criteria for Pearson correlation must be markedly violated.

3) Kendall rank correlation

Pries et al. (2013) performed a Kendall correlation check when determining the relationship between the trading behaviour on financial markets and on Google Trends. Their findings reveal that there is an increase in Google search volumes for particular financial key words; for example "debt" or "stocks" before a stock market falls. Through the use of Kendall tau correlation, they were able to determine that there was an improvement in investment strategy when correlated with financial relevance (using the designated set of financial key words).

In order to determine the strength of correlation, the normal guidelines are as follows:-

	Coefficient, r	
Strength of Association	Positive	Negative
Small	.1 to .3	-0.1 to -0.3
Medium	.3 to .5	-0.3 to -0.5
Large	.5 to 1.0	-0.5 to -1.0

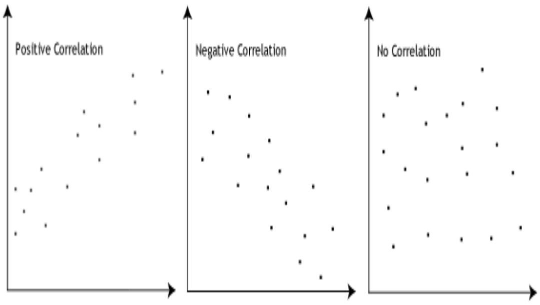

Figure 2.9: Correlation: strength of association, with positive/negative slope.

2.5 Discussion

Through the use of technical analysis, it is possible to determine, within a certain level of probability, what direction a share or stock market index will next take. Several such techniques are mentioned as assisting an investor to determine this; for example, the 30/50 moving average crossover technique (Shipman 2008) or Coppock indicator (Gillen 2012). The Coppock indicator has a proven track record of achieving a positive return to the investor over the long term when used with monthly data. This indicator can also be used to work with more frequent data, but has a tendency to provide a false signal more frequently when used for daily data (Mitchell 2014). Several sources of online web traffic information are available for use, some of which provide a researcher with what the global community is interested in, including Google Trends, Twitter and Wikipedia article traffic statistics. All of these mentioned datasets have been used by researchers in recent times as a successful method of predicting what direction stock markets will take. Wikipedia article traffic statistics have been used to assist in determining the direction of stock markets (Moat et al. 2013).

The fact that people are able to use Wikipedia of their own accord would suggest that there is wisdom to be gained from using the collective information stored in Wikipedia article traffic statistics. In order to remove the noise from highly volatile data such as Wikipedia article traffic statistics, a method of applying the Smoothed rate of change (SROC), as advocated by Schutzman (1991), removes the unnecessary noise from the data, resulting in more definite signals from the data. Applying the SROC against the Wikipedia data brings the result in line with the Coppock indicator, as both are categorised as momentum indicators. The available literature suggests that there is a lack of techniques concerning the confirmation of the signal given by the Coppock indicator. Through an investigation of correlations between Wikipedia article traffic statistics and the Coppock indicator, and an examination of the strength of association that exists between the two datasets, it may be possible to determine, for certain stocks and indexes over specific time frames, whether the Wikipedia statistics can be used to confirm the signal provided by the Coppock indicator. The aim of this research is to determine the optimum time frames where the strongest correlation exists, and for which stocks or indexes these strong correlations are present.

3. EXPERIMENTAL DESIGN

3.1 Introduction

This chapter outlines the design of the experiment being carried out as part of the research topic. A detailed account of the data used is provided along with information regarding the cleansing and transformations required in order to produce a complete data set ready for analysis. Details of how to determine the most suitable correlation methodologies to be used, the data involved and the results achieved through this investigation are also discussed.

3.2 Focus of the experiment

The focus of this experiment concerned and tests the correlations that exist between the two datasets, Wikipedia article traffic statistics and the Coppock indicator. This verifies whether the Wikipedia data can be used to confirm the signal given by the Coppock indicator. Several transformations of each set of data were performed to determine whether there was a correlative improvement between the two datasets, thus improving the signal confirmation ability of the Wikipedia statistics. This experiment focused on each of the source datasets, Wikipedia article traffic statistics and the Coppock indicator (derived from daily closing quoted prices). Details are provided in regard to determining the most suitable correlation method used, followed by an exercise in determining the correlation between the two datasets. This includes the choice of any of the following correlation techniques: those of Pearson, Spearman or Kendall. An explanation is given in regard to which of these techniques was chosen to determine the relationship between the two datasets.

3.3 Data

The data used for this experiment was extracted from the following openly available websites:

1. Yahoo Finance Website (finance.yahoo.com).
2. Bloomberg Finance Data (used to fill missing data from Yahoo Finance).
3. Wikipedia Article Traffic Statistics (stats.grok.se).

3.3.1 Financial data structure

The structure of the data downloaded from Yahoo Finance of Bloomberg was as follows:

Field	Format	Source
Date	MM/DD/YYYY	Both
Open	99999.99	Both
High	99999.99	Both
Low	99999.99	Both
Close	99999.99	Both
Volume	99999999999	Both
Adj Close	99999.99	Yahoo Only

Table 3.1: Structure of data downloaded directly from Yahoo Finance or Bloomberg Data.

Of these fields, the Date and Close (from Bloomberg) or Adjusted Close (from Yahoo Finance) was required for further analysis. Therefore, the resultant set of financial price data was as follows:

Field	Format	Description
Date	MM/DD/YYYY	Date of share price (excluding weekends and bank holidays)
Adj Close	999999.99	Closing Price (adjusted for dividends and splits)

Table 3.2: Structure of financial data for each index and share.

For each index or company being analysed, a separate CSV file was created. These would be loaded in the RStudio (Interface for the R Programming Language) for analysis and correlation checks.

Stock Price Filename
Allianz_Price_Data.csv
BASF_Price_Data.csv
Bayer_Price_Data.csv
DAX_Price_Data.csv
DJIA_Price_Data.csv
EON_Price_Data.csv
ExxonMobil_Price_Data.csv
GeneralElectric_Price_Data.csv
Microsoft_Price_Data.csv
ProcterGamble_Price_Data.csv
Siemens_Price_Data.csv
Walmart_Price_Data.csv

Table 3.3: File names containing stock market price data.

The data provided by Yahoo Finance consisted of prices which included dividend and share split information. A dividend is given by a large number of quoted companies as a return in investment to the investor for owning shares, and is given when that company is operating profitably. A share split occurs when a share price has grown positively but needs to be diluted to render it more liquid and available on the market. Each of these events can happen at various periods during the year. In order to account for any dividend payments and stock splits, the prices provided by Yahoo Finance are inherently adjusted to reflect these occurrences. This was chosen, as it means that the price smoothens out the influence of these events. If the dividends or splits are not factored into the prices prior to the event, it will appear that there was a large increase or decrease in the share price. This could give a false signal from a technical analysis and a correlative point of view, and therefore distort the reality of events which reflect the share price and any correlation that can be obtained from the data.

Two separate years of data for each data source, 2008 and 2014, were used as part of this experiment. 2008 was chosen due to the high volatility occurring during the beginning of the financial crisis, particularly with the collapse of Lehman Brother in

September, 2008. This was also the first year when a complete set of yearly data was recorded for Wikipedia article traffic. Following this, a more recent set of data for 2014 was used to determine the correlative relationship between the two sets and to discover, due to the increase in Wikipedia traffic in 2014, whether the same correlative relationships remained.

Financial datasets

The Dow Jones Industrial Average and DAX German Exchange were chosen due to their characteristic similarity of being comprised of 30 large capitalised stocks, and also because they relate to different continents. This presented an opportunity to determine correlation behaviours between both indexes and their associated selected shares. For each of these stock exchanges, five of the largest capitalised stocks were selected using the market capital weighting of the stock on its associated exchange. This selection process was facilitated through the use of Wikipedia (Wikipedia.org), WikiInvest (wikiinvest.com) and Wolfram Alpha (wolframalpha.com). As a result, the five stocks per stock market exchange were selected as follows:

German DAX Exchange

Company	Industry	Ticker Symbol	Index Weighting (%)
Siemens	Electronics	SIE	9.96
BASF	Chemicals	BAS	9.62
Bayer	Pharma	BAYN	7.55
Allianz	Insurance	ALV	6.66
E.ON	Energy	EOAN	6.24

Table 3.4: List of highest weighted stock on German DAX Exchange.

Dow Jones Industrial Average (DJIA) Exchange

Company	Industry	Ticker Symbol	Index Weighting (%)
ExxonMobil Corp.	Oil and Gas	XOM	10.66
General Electric Co.	Conglomerate	GE	7.90
Microsoft Corp.	Software	MSFT	6.76
Wal-Mart Inc.	Retail	WMT	6.24
Procter & Gamble Co.	Consumer Goods	PG	5.93

Table 3.5: List of highest weighted stocks on Dow Jones Industrial Average Exchange.

3.3.2 Wikipedia data structure

This data was obtained from the Wikipedia Article Traffic Statistics website (stats.grok.de), which collects traffic on Wikipedia page views and page edits. These web views and edits for each Wikipedia page are recorded for a designated set of spoken languages. This page count recording is produced each hour of every day, 365 days per year. In this experiment, the focus of attention is on page views and pages in the English language only.

There were two means of obtaining data from the Wikipedia Article Traffic Statistics website (stats.grok.de):

a) Raw data in fixed field length format

Field	Comments
Language	i.e. 'en' for English
Page Visited	Title of Page Retrieved
Number of Visits	Number of Requests for Page
Size of content returned (in bytes)	Size of Page Returned

Table 3.6: Structure of raw data files, stored by the hour.

Each data file, for all pages and languages, is archived every hour, 365 days per year. Therefore, in order to obtain data for specific pages over a particular time frame, a full download of data for each year being analysed is required. For 2008, this equates to an approximated full download of 300 GB of data. This was deemed to be too laborious a means of obtaining the subset of data required for this piece of research.

b) Raw data in the JSON (JavaScript Object Notation) format

An alternative method of downloading was to obtain data specific to the pages in question – in this case, companies and stock market indexes. Therefore, for each page queried and each associated month, there was a facility provided to download that data in JSON format. The structure of this data was as follows:

{}JSON

- *{} Daily_Views*
  - *YYYY-MM-DD: 9999 (Number of Views) - 1 record per day for 1 month.*

This was the preferred method, as it meant that only the required data was downloaded, thus reducing the overall download capacity and duration. For each company/index, the JSON file was downloaded ready for transformation into CSV format.

As illustrated in Figure 3.1 below, each company or index being analysed was queried via the Wikipedia article traffic statistics GUI. This data was subsequently downloaded in the JSON format.

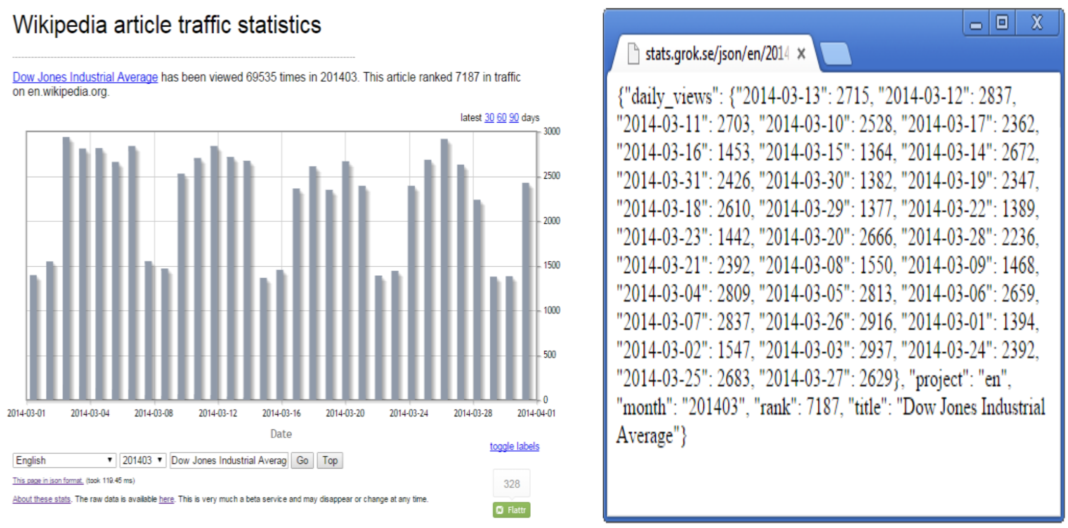

Figure 3.1: Example Wikipedia article traffic statistic (Visual and JSON) on Dow Jones page.

Once the JSON structured data was downloaded for each relevant Wikipedia page, the following data cleansing was performed to create an associated CSV structured file, suitable for loading into the R Programming Language:

1) The header and trailer records were removed in each monthly extract.
2) Double quotes enclosing each date were cleared.
3) Colon delimitation was replaced with a comma.

This resulted in a set of CSV files, one for each share and index, where each file contained the daily breakdown of the page view for each required Wikipedia page. This file consisted of the following structure:

Field	Format	Description
Date	DD/MM/YYYY	Date of Page Count (including weekends and Bank Holidays
No. of Views	9999999	Number of Page Views (non unique per user count)

Table 3.7: Structure of Wikipedia article traffic statistics for each index and company.

One CSV file was created for each company and index, which consisted of data for each day of the year, including weekends and public holidays, named as follows:

Wiki Statistics Filename
Allianz_Wiki_Stats.csv
BASF_Wiki_Stats.csv
Bayer_Wiki_Stats.csv
DAX_Wiki_Stats.csv
DJIA_Wiki_Stats.csv
EON_Wiki_Stats.csv
ExxonMobil_Wiki_Stats.csv
GeneralElectric_Wiki_Stats.csv
Microsoft_Wiki_Stats.csv
ProcterGamble_Wiki_Stats.csv
Siemens_Wiki_Stats.csv
Walmart_Wiki_Stats.csv

Table 3.8: Filenames containing associated Wikipedia article traffic statistic data.

As a result, each of these datasets was in a state ready to be loaded in the R Programming Language via RStudio.

Wikipedia datasets

For the purpose of this research, the following sets of data were processed:

- <u>October 1st 2013 to December 2014</u>

  Due to the fact that the raw data was transformed in order to allow for different correlation checks, a number of months prior to each year being analysed were downloaded. Therefore, for 2014, data from 1st October 2013 to 31st December 2014 was downloaded.

- <u>December 10th 2007 to December 31st 2008</u>

  Similarly, a set of data prior to the year being analysed was required. Because the recording of Wikipedia article traffic statistics began on 10th December 2007, data from that first available date was downloaded.

Through the Wikipedia article traffic statistics (stats.grok.de) website, it was possible to obtain an initial visualisation of the article traffic activity for any month/year combination, and to extract this for each day of that chosen month/year, since December 2007. Through this GUI, an option to download that presented data in the JSON format was granted. Therefore, data for all months in 2008 and 2014 against each relevant particular Wikipedia page was selected and downloaded. A sample output of a file used in this experiment is presented in Appendix A. Due to Wikipedia's facilitation of multiple languages; it is also possible to obtain the page views for other languages. For the purpose of this research exercise, and due to the fact that the English language is the most commonly used on Wikipedia[12], the English language was chosen.

3.4 Data Cleansing

The majority of data (stock and index) provided by Yahoo Finance was consistent and clean, with the following exceptions:

i. Missing price data concerning German shares between 29th July 2008 and 15th August 2008. To fill this data gap, data from Bloomberg was obtained for each

[12] "Page Views for Wikipedia (2015) [Online]. Available: http://stats.wikimedia.org/EN/TablesPageViewsMonthlyOriginalCombined.htm [Accessed 7 January 2015]."

day, and filled accordingly.

ii. Wikipedia Article Traffic Statistics contains data for all days of the week, 365 days per year. The associated stock market data does not exist for weekends and public holidays. Therefore, in order to retain the value of weekend Wikipedia View Data, during the processing of each set of files (financial and Wikipedia data), it was decided to fill each stock market missing day, whether involving a weekend or a public holiday, with the last closing price available (normally the Friday closing price).

iii. Missing Wikipedia Article Traffic Statistics data from 15th July 2008 to 30th July 2008. Due to the fact that the data exhibited trends and seasonality, with weekdays generally busier than weekends, the Holt-Winters approach was chosen to forecast the missing values. As the period of missing data followed a sufficient period of time where data existed, it was possible to use the Holt-Winters approach to obtain a set of forecasted values to fill this period of missing data.

3.5 Transformation of data

The facilitation of missing data and details of the techniques used to assist in best populating this data were investigated. Transformations applied to the stock market prices in order to calculate the Coppock value, along with the different parameters used, were executed. Other transformations applied to both the price data and Wikipedia data, in order to determine any improvement in correlation between the two datasets, were also executed. In order to select the most suitable correlation technique, the Shapiro-Wilks test for normality was performed. Once identified, a series of correlation checks were executed against different states of data (raw and transformed) over a set of different time ranges. Different time ranges of three months, six months, nine months and 12 months, each beginning on the 1^{st} January of the year in question, were evaluated in order to identify the correlation behaviour between the datasets.

Normality checks

In order to determine the most suitable correlation technique, the Shapiro-Wilks Normality check was chosen over the following time frames:

From Date	To Date
1/1/2008	31/3/2008
1/1/2008	30/6/2008
1/1/2008	30/9/2008
1/1/2008	31/12/2008
1/1/2014	31/3/2014
1/1/2014	30/6/2014
1/1/2014	30/9/2014
1/1/2014	31/12/2014

Table 3.9: Time frames by which normality check was performed on the Wikipedia and financial price data.

The basic principle is that, in order to perform the Pearson correlation against two sets of data, each set of data must return a p-value >= 0.05. If the p-value is less than 0.05, the null hypothesis is rejected, and there is, therefore, evidence that the data does not come from a normally distributed population. Alanyali et al. (2013), when investigating relationships between financial news and the stock market, used the Spearman rank correlation to uncover links between company mentions in the news on a given morning and trading volumes later that day. Qie (2011), in a study to determine the correlation between market volatility and portfolio managers' performance, concluded that using the Spearman rank correlation was the most suitable alternative for reflecting this relationship. Therefore, in this research, the chosen method of determining the relationship between Wikipedia article traffic statistics and financial price data is through the use of the Spearman rank correlation.

The R Programming Language function "*shapiro.test*" (Package: stats), was used to determine the normality of a dataset. A sample of the results from this test can be viewed in Figure 3.11, below. This is representative of the p-values that were returned. As can be seen, the majority of p-values were below the alpha value of 0.05. Those that were above the threshold are highlighted in yellow. A minority of cases, highlighted in blue, involved both datasets being above the alpha value threshold of 0.05, and thus could, therefore, have the Pearson correlation check applied.

3 month data set - January 2008 to March 2008 - Shapiro-Wilk results					
Company	**Raw Wiki**	**Log10 Wiki**	**SROC Wiki**	**Raw Price**	**SW Coppock**
Allianz_Price_Data.csv	0.3778294484	0.0003822103	0.0000000398	0.0000000445	0.0157709688
BASF_Price_Data.csv	0.1683041514	0.0002108233	0.0000120749	0.0000000000	0.0000000000
Bayer_Price_Data.csv	0.0315005816	0.0000000909	0.0294069351	0.0002097663	0.0000020619
DAX_Price_Data.csv	0.0176537500	0.0007076528	0.0000008457	0.0000008893	0.0000039573
DJIA_Price_Data.csv	0.0128737754	0.0067951770	0.0000001588	0.0772825571	0.0003956415
EON_Price_Data.csv	0.0039089922	0.0012009670	0.0000003399	0.0000000336	0.0000029724
ExxonMobil_Price_Data.csv	0.0029495136	0.3873591734	0.0001453240	0.0015550183	0.1061568921
GeneralElectric_Price_Data.csv	0.0028294650	0.0000032111	0.0000000020	0.0000938042	0.0000000254
Microsoft_Price_Data.csv	0.0000323515	0.0091914089	0.0153581699	0.0000000111	0.0022226403
ProcterGamble_Price_Data.csv	0.0000000000	0.0002219606	0.0000000147	0.0000004988	0.0006199852
Siemens_Price_Data.csv	0.0000000000	0.0005670832	0.0000074165	0.0002933750	0.0000599809
Walmart_Price_Data.csv	0.0000000000	0.2560039531	0.0000000337	0.0342956796	0.2901326359

Table 3.10: Sample of Shapiro-Wilk Normality test for each set of data (Raw and Transformed).

Software used

This experiment was designed and implemented using the R Statistical Programming Language, using RStudio. Rattle, which provides a data-mining graphical user interface executing on top of the R Programming Language, was used to complement the work done through RStudio. An Oracle database (version 11g) was used to perform some post-processing analysis and reporting on the result data.

Sample design

Initial analysis was performed on the complete year of 2008. Due to the noisy nature of the Wikipedia article traffic statistics data, a process of smoothening the data by using the Smoothed rate of change (SROC), as recommended by Elder (1993), was performed. In order to achieve the optimal usage of the 2008 window of time, all data from the earliest available date on Wikipedia was obtained. As this data was from 10th December 2007 onwards, the consequence of this resulted in the first Smoothed ROC value beginning on 12th January 2008. Financial price data was available for all of 2007. Therefore, any corresponding raw price or derived (Coppock) results were available to match the commencement date of the Wiki data.

For the analysis of 2014, there was no restriction on the Wikipedia data availability. Therefore, data from October 2013 to December 2014, inclusive, was downloaded and transformed. This provided both raw and transformed data from 1st January 2014. Similarly, the corresponding financial data was downloaded in order to allow both raw and transformed data to commence on 1st January. Tests for normality which applied the Shaprio-Wilk test were performed on each dataset (raw and transformed). Dependent on the results from the Shapiro-Wilks test, the appropriate correlation checks were performed. Based on the correlations obtained, conclusions were made in order to determine the viability of using Wikipedia article traffic statistics as a means of verifying the signal given by the Coppock indicator.

3.6 Summary

A description of the focus of this experiment, along with details of the two datasets, was presented. These datasets consisted of the financial price data which was used to derive the Coppock indicator and the Wikipedia article traffic statistics. Data cleansing and transformation of the data were discussed. The structure of each data set was outlined, along with the use of the Shaprio-Wilk normality check used to determine the most suitable correlation technique to use against the two datasets.

4. EXPERIMENTATION AND EVALUATION

This chapter discusses the data pre-processing performed on the datasets in order to allow the suitable correlation checks to be performed between the two datasets. Details of the results of the normality check in order to select the most appropriate correlation techniques are discussed. Finally, the results from the chosen correlation check between the financial dataset (Coppock values) and the Wikipedia article view statistics are outlined.

4.1 Data pre-processing and initial characteristic analysis

4.1.1 Missing stock price data

Some financial price data was unavailable from Yahoo Finance between 29th July 2008 and 15th August, inclusive, for each of the following German (DAX) stocks:

- Siemens
- Allianz
- BASF
- Bayer

An alternative source of data was available from Bloomberg[13]. Bloomberg data, unlike Yahoo Finance data, is not adjusted for dividends and splits. Therefore, using the Bloomberg price given and the daily percentage rise or fall derived from this, it was possible to derive the associated missing adjusted price data from the last available Yahoo Finance price. This was achieved by applying the percentage gain/loss calculated through the Bloomberg data against the last most recent Yahoo Finance price provided. This was repeated for each day up until the next reliable Yahoo Finance price was available. Therefore, the end result was a complete set of adjusted prices with the correct share split and dividend factored in.

[13] "Bloomberg Data [Online]. Available: http://www.bloomberg.com/markets/stocks/world-indexes [Accessed 10 January 2015]."

The example provided in Table 4.1, below, outlines an example using Siemens (SIE.DE). Considering the close price from Bloomberg, it was possible to calculate the "% Gain/Loss". This "% Gain/Loss" was then applied to the last available Yahoo value (as of 28th July 2008) and repeated for each missing adjusted value. As a result, it was possible to calculate the adjusted close price. To verify the success of this process, the last derived close price was reconciled with the first associated available close price on Yahoo Finance. These figures matched, indicating that each daily derivation was correct. This derived data was then populated into full data set for that company and repeated for each subsequent company (Allianz, BASF and Bayer).

Siemens (SIE.DE)				
Date	**Close**	**Adj Close**	**% Gain/Loss**	**Comment**
7/28/2008	70.25	57.26		**Last Available Value**
7/29/2008	70.95	57.83	1.00	**Derived**
7/30/2008	75.05	61.17	5.78	**Derived**
7/31/2008	76.32	62.21	1.69	**Derived**
8/1/2008	74.69	60.88	-2.13	**Derived**
8/4/2008	74.09	60.39	-0.80	**Derived**
8/5/2008	75.65	61.66	2.11	**Derived**
8/6/2008	76.55	62.40	1.19	**Derived**
8/7/2008	76.55	62.40	0.00	**Derived**
8/8/2008	76.81	62.60	0.33	**Derived**
8/11/2008	76.92	62.70	0.15	**Derived**
8/12/2008	75.54	61.57	-1.80	**Derived**
8/13/2008	73.38	59.82	-2.85	**Derived**
8/14/2008	73.54	59.94	0.21	**Derived**
8/15/2008	73.96	60.28	0.57	**Derived**
8/18/2008	74.39	60.64	0.59	**Derived**
8/18/2008	74.39	60.64		**Next Available Value**

Table 4.1: Derivation of adjusted close price from Bloomberg close price.

4.1.2 Missing weekend stock market price data

Because the German (DAX) and US (DJIA) markets normally close on Friday and reopen on Monday, data was missing for weekends and public holidays. However, Wikipedia article traffics statistics continue to be recorded regardless of whether it is a weekend or public holiday. Therefore, in order to perform correlation checks between the finance data and associated Wiki data, each set had to contain the same number of records to function correctly. The method used to fill the weekend and appropriate bank holiday data was to take the last close price, normally Friday, and fill it into the missing weekend data. This resulted in the Wikipedia and finance datasets containing the same number of records.

4.1.3 Missing Wikipedia article traffic statistics data

A set of missing data existed between 13th July 2008 and 31st July 2008, inclusive, representing 19 days of missing data. This was consistent across all datasets. One consideration was to delete the associated financial data in order to allow the correlation process to execute, but there was a risk of losing important knowledge value from the data as a consequence. Therefore, a suitable methodology was required to best fill the data. Because the data had a weekly seasonality, Holt-Winters forecasting (Chatfield and Yar 1988) was chosen as the best method of populating this missing data for each company/index being analysed.

R provided a function called "forecast.HoltWinters" ("fma" and "forecast" R packages required) to derive the missing values based on an existing prior set of seasonal data. In order to achieve the optimum forecast, it was important to include a sufficient set of seasonal, historic data from which Holt-Winters could forecast. Because the seasonality, in this case, was weekly, data from 1st June 2008 to 12th July was used. The frequency of data was set to seven days (one week). The resulting set of data produced for the missing range of data for each stock/index resembled the following:

	Point Forecast
7.000000	651.4082
7.142857	784.3013
7.285714	966.1698
7.428571	885.6122
7.571429	1057.2645
7.714286	849.3358
7.857143	682.6096
8.000000	608.5034
8.142857	741.3965
8.285714	923.2650
8.428571	842.7075
8.571429	1014.3597
8.714286	806.4310
8.857143	639.7049
9.000000	565.5987
9.142857	698.4918
9.285714	880.3602
9.428571	799.8027
9.571429	971.4550

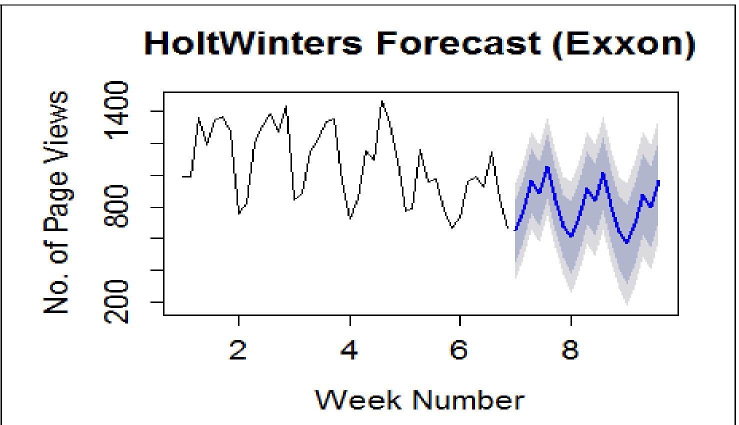

Figure 4.1: Raw Holt-Winters forecasted data for ExxonMobil and associated chart (forecasted values in blue).

The raw data returned by Holt-Winters for each stock/index was then included in the relevant Wikipedia dataset.

4.1.4 Coppock value derivations

In order to perform the correlation between the financial dataset and its associated Wikipedia dataset, a number of pre-processing steps were performed to facilitate this. As mentioned by Gillen (2012), the original Coppock indicator is the sum of a 14-month rate of change (ROC) and the 11-month rate of change, which is then smoothed by a 10-period weighted moving average (WMA). Because the data frequency being processed was daily, in order to determine any correlative improvement between the Coppock values and the associated Wikipedia data, the Coppock values were initially derived using the standard parameters adopted by the monthly calculation.

Following this, two further derivations of the Coppock values were created using parameters recommended by Mitchell (2014) and StockCharts.com (2015). Based on this, the next set of Coppock values was generated using the 14-day and 11-day ROCs, Smoothed by the 6-day WMA. By decreasing the WMA, the signal to enter and exit trades was provided slightly earlier, which is often suited to daily data. Finally, a third set of Coppock values was created using the 20-day and 10-day ROC, Smoothed by the 10-day WMA. These settings make the Coppock curve a little less sensitive, which is also suited to daily charts.

Coppock Value Parameters			
Data Set	**ROC 1**	**ROC 2**	**WMA**
Coppock Set 1	14	11	10
Coppock Set 2	14	11	6
Coppock Set 3	20	10	10

Table 4.2: Set of Coppock values derived from financial prices.

Each set of Coppock values was used to determine the optimal correlation that could be achieved between this and the associated Wikipedia dataset. Figure 4.2, below, demonstrates the raw price data of the DAX Index for 2008, along with the associated Coppock curve.

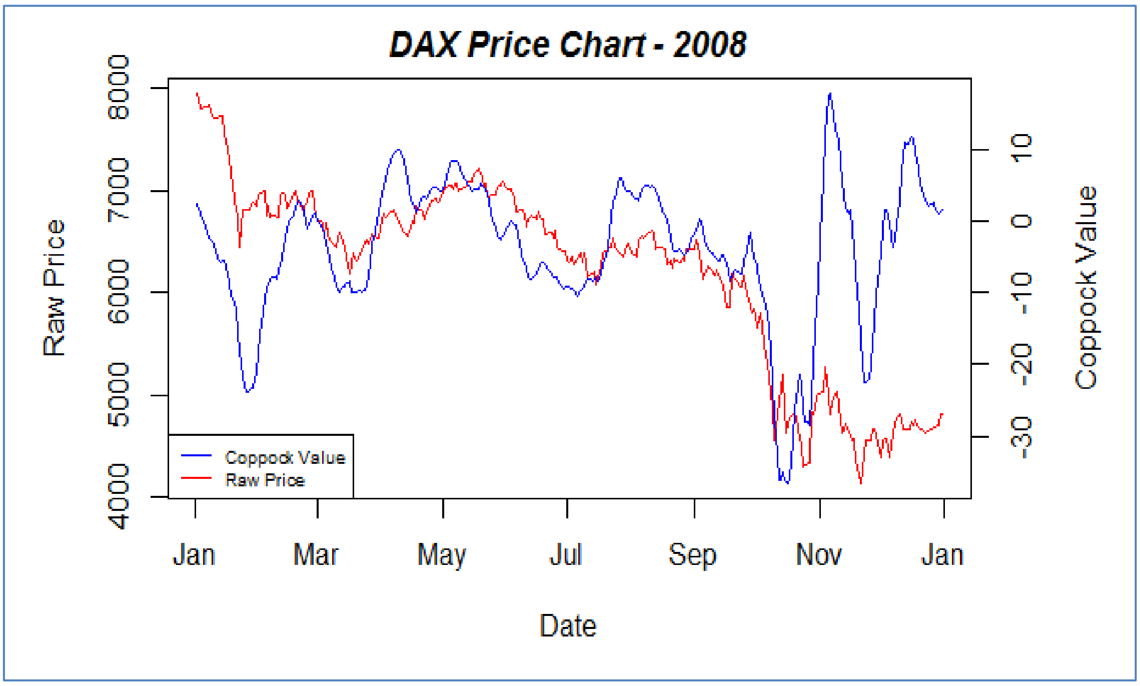

Figure 4.2: Example of Coppock curve derived from the DAX index price data for 2008.

In order to calculate the Coppock values for each full year in question, 2008 and 2014, where the first Coppock value begins on 1st January and ends on 31st December, a set of stock price data from each previous year (2007 and 2013) was required. Due to the availability of this stock price data from Yahoo Finance, there was no limitation in generating the Coppock values commencing on 1st January. In the example given in Figure 4.4, to derive the Coppock values that commenced on 1st January 2008 using the default 14 ROC/11 ROC/WMA 10 parameters, the underlying stock price data was required from 7th December 2007.

Date	Price	ROC_11	ROC_14	Total ROC	Coppock
12/7/2007	13625.58	NA	NA	NA	NA
12/8/2007	13625.58	NA	NA	NA	NA
12/9/2007	13625.58	NA	NA	NA	NA
12/10/2007	13727.03	NA	NA	NA	NA
12/11/2007	13432.77	NA	NA	NA	NA
12/12/2007	13473.9	NA	NA	NA	NA
12/13/2007	13517.96	NA	NA	NA	NA
12/14/2007	13339.85	NA	NA	NA	NA
12/15/2007	13339.85	NA	NA	NA	NA
12/16/2007	13339.85	NA	NA	NA	NA
12/17/2007	13167.2	NA	NA	NA	NA
12/18/2007	13232.47	-2.88508819	NA	NA	NA
12/19/2007	13207.27	-3.07003445	NA	NA	NA
12/20/2007	13245.64	-2.78843176	NA	NA	NA
12/21/2007	13450.65	-2.01339984	-1.283835257	-3.2972351	NA
12/22/2007	13450.65	0.13310732	-1.283835257	-1.15072794	NA
12/23/2007	13450.65	-0.17255583	-1.283835257	-1.45639109	NA
12/24/2007	13550.04	0.23731391	-1.289353924	-1.05204001	NA
12/25/2007	13550.04	1.5756549	0.873014278	2.44866918	NA
12/26/2007	13551.69	1.58802385	0.57733841	2.16536226	NA
12/27/2007	13359.61	0.1481276	-1.171404561	-1.02327696	NA
12/28/2007	13365.87	1.50882496	0.195054667	1.70387963	NA
12/29/2007	13365.87	1.00812622	0.195054667	1.20318089	NA
12/30/2007	13365.87	1.20085377	0.195054667	1.39590844	0.769369198
12/31/2007	13264.82	0.14480237	0.741387691	0.88619006	0.913452312
1/1/2008	13264.82	-1.38156892	0.244474388	-1.13709453	0.613603225

Table 4.3: Sample of calculation of Coppock value on the DJIA index price using ROC and WMA.

Wikipedia data transformations

The earliest Wikipedia article traffic statistics (WATS) data was available from 10th December 2007. Therefore, it was possible to check direct correlations between the Raw Wiki data against the derived Coppock data from 1st January of each year (2008 and 2014). Due to the fact that the Wikipedia data appeared noisy (refer to Figure 4.3), a recommended method of obtaining fewer but better quality signals, as advocated by Elder (1993), was through the application of the Smoothed rate of change (SROC) on the raw data.

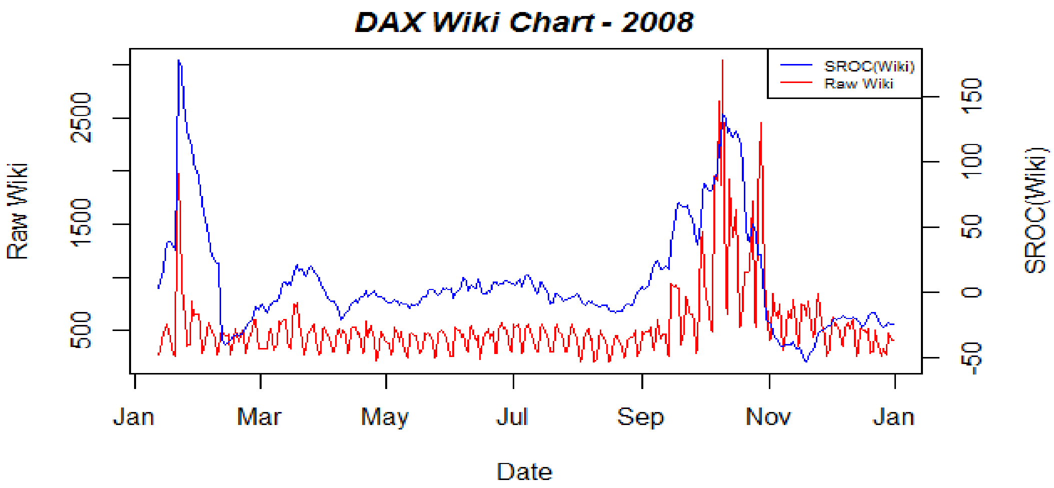

Figure 4.3: Example of SROC applied to the raw Wiki data of the DAX page.

This was achieved by applying the exponential moving average (EMA), followed by a rate of change (ROC), on the raw data. The application of both the EMA and ROC provided a means of highlighting whether a trend was accelerating, slowing down or progressing at the same speed. Invented by Schutzman (1991), this Smoothed rate of change overcame the major flaw of ROC, so that each data value was responded to only once, rather than twice. The SROC compared the values of an EMA, instead of prices at two points in time, which provided a more definite signal and fewer false signals. In order to use this SROC over the Wikipedia article view statistics, Elder recommended calculating the 13-day EMA, followed by the 21-day ROC. It was therefore possible to obtain fewer but more effective signals from the Wikipedia data through the use of SROC. Because the earliest Wikipedia data was available from 10th December 2007, the earliest resulting SROC value, using the recommended 13-day EMA and 21-day ROC, occurred on 12th January 2008 (refer to Table 4.4).

Date	WikiStats	EMA	Momentum_EMA		Date	WikiStats	EMA	Momentum_EMA
10/12/2007	2286	NA	NA		28/12/2007	1401	1407.404	NA
11/12/2007	2687	NA	NA		29/12/2007	995	1348.489	NA
12/12/2007	2839	NA	NA		30/12/2007	889	1282.848	NA
13/12/2007	2116	NA	NA		31/12/2007	1402	1299.869	NA
14/12/2007	1813	NA	NA		01/01/2008	1223	1288.888	NA
15/12/2007	1063	NA	NA		02/01/2008	2105	1405.476	NA
16/12/2007	1062	NA	NA		03/01/2008	2214	1520.979	NA
17/12/2007	1905	NA	NA		04/01/2008	2499	1660.696	NA
18/12/2007	1916	NA	NA		05/01/2008	1608	1653.168	NA
19/12/2007	1741	NA	NA		06/01/2008	1412	1618.716	NA
20/12/2007	1642	NA	NA		07/01/2008	2296	1715.471	NA
21/12/2007	1398	NA	NA		08/01/2008	2704	1856.689	NA
22/12/2007	864	1794.769	NA		09/01/2008	2842	1997.448	NA
23/12/2007	714	1640.374	NA		10/01/2008	2578	2080.384	NA
24/12/2007	1028	1552.892	NA		11/01/2008	2856	2191.186	NA
25/12/2007	793	1444.336	NA		12/01/2008	1893	2148.588	19.71389172
26/12/2007	1244	1415.716	NA		13/01/2008	1511	2057.504	25.42899051
27/12/2007	1365	1408.471	NA		14/01/2008	2640	2140.718	37.85364497

Table 4.4: Example of first available Smoothed rate of change on WATS for January 2008.

Therefore, in order to perform the appropriate Pearson/Spearman or Kendall correlation checks, it was necessary that each dataset (financial price and Wikipedia SROC) was of the same size and structure. As a result, the correlations between the financial data (raw or Coppock) and Wiki SROC values for 2008 could only be performed on each dataset between 12th January 2008 and 31st December 2008. This was not an issue for the 2014 datasets, due to the availability of pre-2014 data for both the Wikipedia data and associated stock price data. As a result, for 2014, this allowed for the correlation checks between all datasets to commence on 1st January 2014 and end on 31st December 2014.

4.1.5 Correlation checks

As a result of the normality checks performed during the design stage of the dissertation and the completion of the Shapiro-Wilks test, conclusions were made to determine what correlation methods would be applied to each respective dataset for each date range. Initial analysis, however, indicated that the Spearman rank order correlation check would be the most suitable in most cases, and thus would be performed against the majority of dataset combinations. In cases where the normality test allowed for Pearson correlation, these would be executed. The following table outlines each available dataset, be it raw or transformed, and the corresponding datasets that will be correlated against it.

Dataset 1 - Wikipedia Data	Dataset 2 - Share Price Data
Wikipedia Page View Counts (Raw Wiki Data)	Stock Price (Raw Price Data)
Log 10 on Wikipedia Page Views	Coppock Values (14ROC/11ROC/10WMA parameters)
SROC on Wikipedia Page Views (13EMA/21ROC parameters)	Coppock Values (14ROC/11ROC/6WMA parameters)
	Coppock Values (20ROC/10ROC/10WMA parameters)

Table 4.5: Detail of each dataset for correlation check.

For example, a correlation check was performed between the SROC (Wikipedia) and each of the corresponding items in Dataset 2 (share price data). The strongest correlation for this test was obtained and ranked in strength. This exercise was performed for each time frame outlined in Table 4.6, and a table of results produced from this.

From Date	To Date
1/1/2008	31/3/2008
1/1/2008	30/6/2008
1/1/2008	30/9/2008
1/1/2008	31/12/2008
1/1/2014	31/3/2014
1/1/2014	30/6/2014
1/1/2014	30/9/2014
1/1/2014	31/12/2014

Table 4.6: Timeframe for each correlation check.

4.1.6 Strengths and Limitations

<u>Strengths</u>

i. Due to the fact that both the Smoothed Rate of Change and Coppock Indicators are momentum indicators, means that the data is in a compatible state for correlation checking and more likely to achieve optimal strengths of association.

ii. A growing set of data being gathered on Wikipedia Article Traffic Statistics means that, as time goes on, a truer picture of community attention will be revealed and may result in improved correlations.

iii. Data is constantly available allow for the facilitation of updated correlations.

<u>Limitations</u>

i. Isolated to one main page on Wikipedia per stock/index which could limit the true audience attention. A solution suggested would be to bring in Wikipedia traffic of pages linked to the main page.

ii. Using Friday Stock close for Weekend and Public holidays

iii. No one consistent set of Coppock Parameters are used throughout, although 20/10/10 account for most optimal correlations in 2008 and 2014.

iv. Each share needs to be more closely analysed using charts etc. to determine individual correlation behaviour.

v. No threshold of correlation to determine what is considering suitable to backup the Coppock Indicator.

4.2 Summary

An explanation of how data was cleansed, either through the use alternative sources of data or the facilitation of non-weekend data for stock market prices was provided. A process of filling missing data within the Wikipedia data source was also provided

With these prepared raw data sets, Wikipedia article traffic statistics and Share Price data, a set of derived datasets were generated for each source. The Coppock values were derived from the share price information using recommended Rate of Change and Weighted Moving Average parameters deemed to create optimal values on daily data. The Smoothed Rate of Change (SROC) was applied to the raw Wikipedia dataset resulting in more distinctive signals.

A Shaprio-Wilk normality test was then conducted for each of the raw and derived datasets for each time frame (three, six, nine and 12 months), and the Spearman correlation check was performed.

5. RESULTS AND DISCUSSION

This chapter reviews the results from the empirical study as described in Chapter 4. These findings are outlined in the following structure:

i. A normality check performed for each of the datasets, raw and derived, as indicated in Chapter 4, for each of the timeframes in question: three-month, six-month, nine-month and twelve-month time frames across the two years analysed, 2008 and 2014.
ii. The most suitable correlation check is subsequently performed against each suitable dataset pair, and the findings outlined.
iii. These results are then summarised and compared to the findings presented in the literature review.

A brief stock market commentary is provided for each period, in order to place the results into the context of the market at that point in time.

5.1 Results

As discussed in Chapter 2, in order to determine the most suitable correlation method to apply against the two datasets, the normality of the data needs to be determined. The following results were obtained for each of the datasets.

5.1.1 *Shapiro-Wilk test for Normalisation on Wikipedia data – 2008*

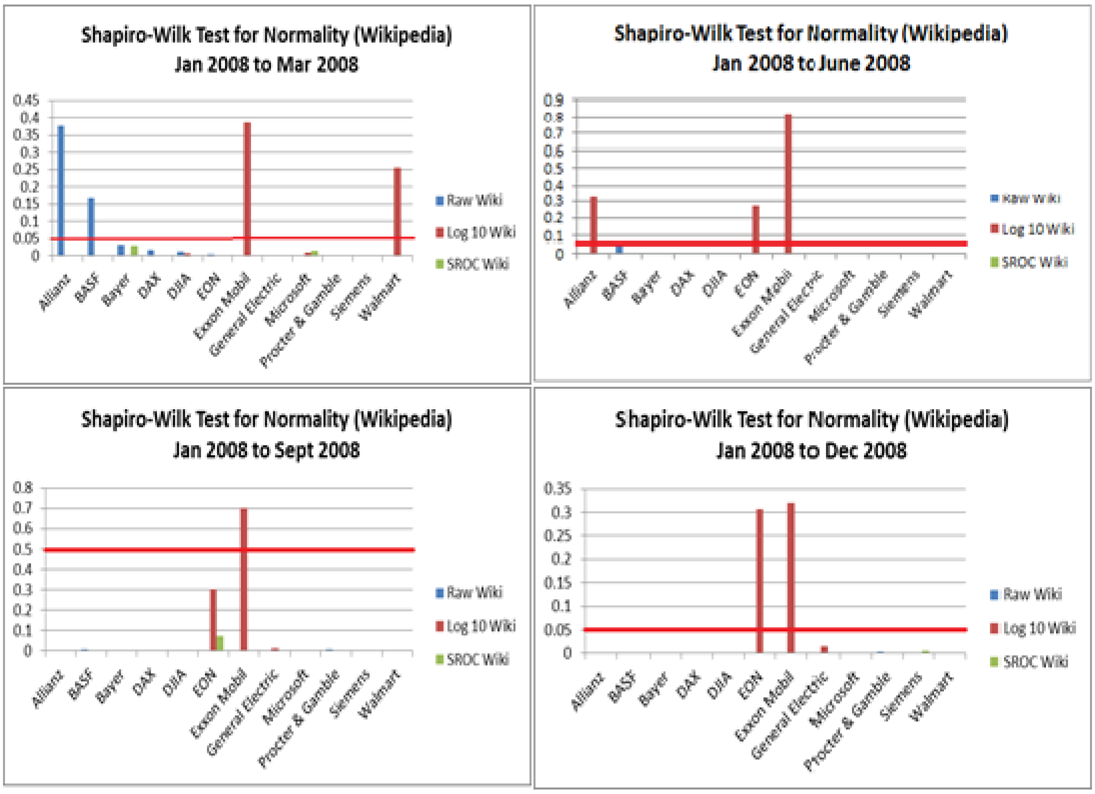

Figure 5.1: Shapiro-Wilk test for normality on Wikipedia article traffic statistics (raw, Log10 and SROC) – 2008.

As can be seen in Figure 5.1, only a small percentage of Wikipedia data for each company and index exceed the alpha value of 0.05. The majority of the datasets fail the Shapiro-Wilk test for normality, and, as a consequence, the Spearman test will be performed in the majority of cases. Those which fail the Shapiro-Wilk test are quite below the p threshold of 0.05. Those which pass the Shapiro-Wilk test are mostly achieved through the Log10 of the corresponding Wikipedia raw data. In addition, a number of datasets pass the Shaprio-Wilk test through the application of the Coppock formula against the raw data, yielding a more normalised dataset.

5.1.2 Shapiro-Wilk test for normalisation on Wikipedia data – 2014

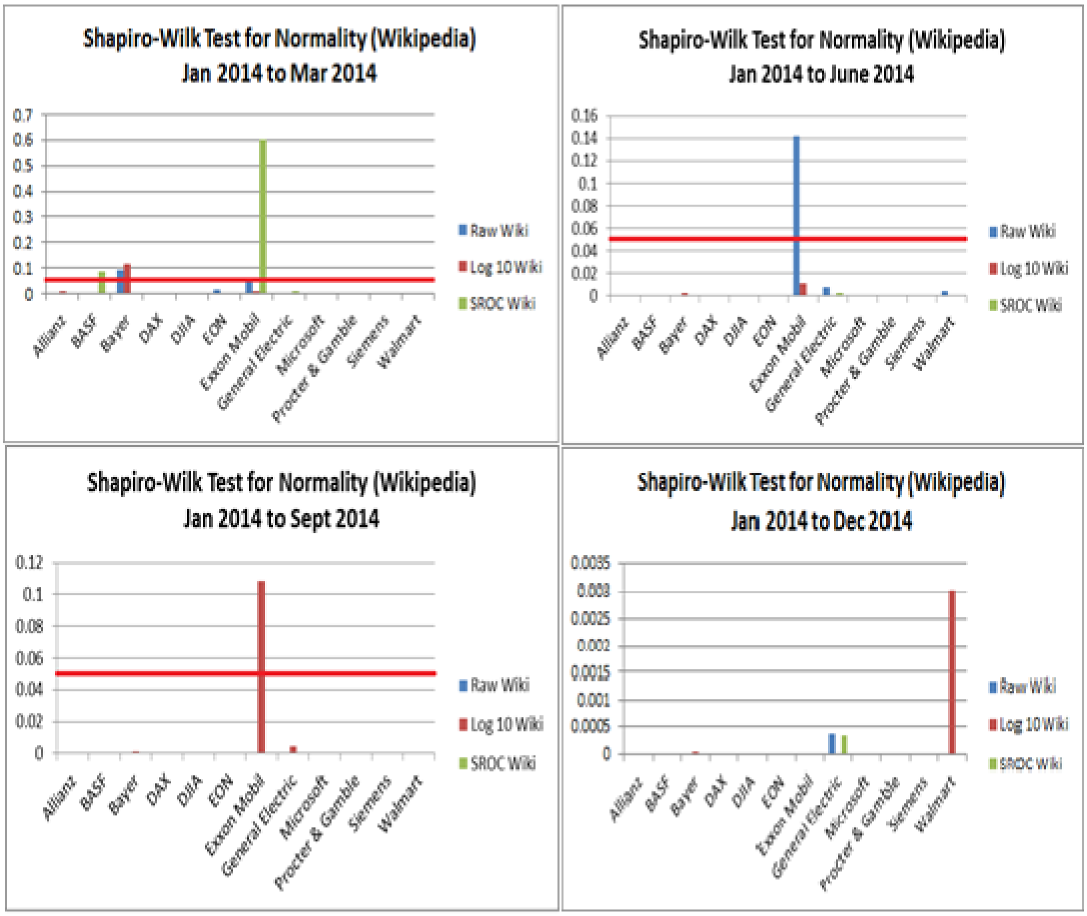

Figure 5.2: Shapiro-Wilk test for normality on Wikipedia article traffic statistics (raw, Log10 and SROC) – 2014.

Similarly, for 2014, against the Wikipedia dataset, only a small percentage of the stocks/indexes pass the Shapiro-Wilk test for normality by exceeding the alpha value of 0.05. In this case, the Exxon Mobil stock appears to pass the normality test when either the raw, Log10 or SROC data are applied to the dataset in each time frame (three, six and nine months). All other shares and indexes are below the 0.05 threshold, and are deemed not to be normalised.

5.1.3 Shapiro-Wilk test for normalisation on stock price data – 2008

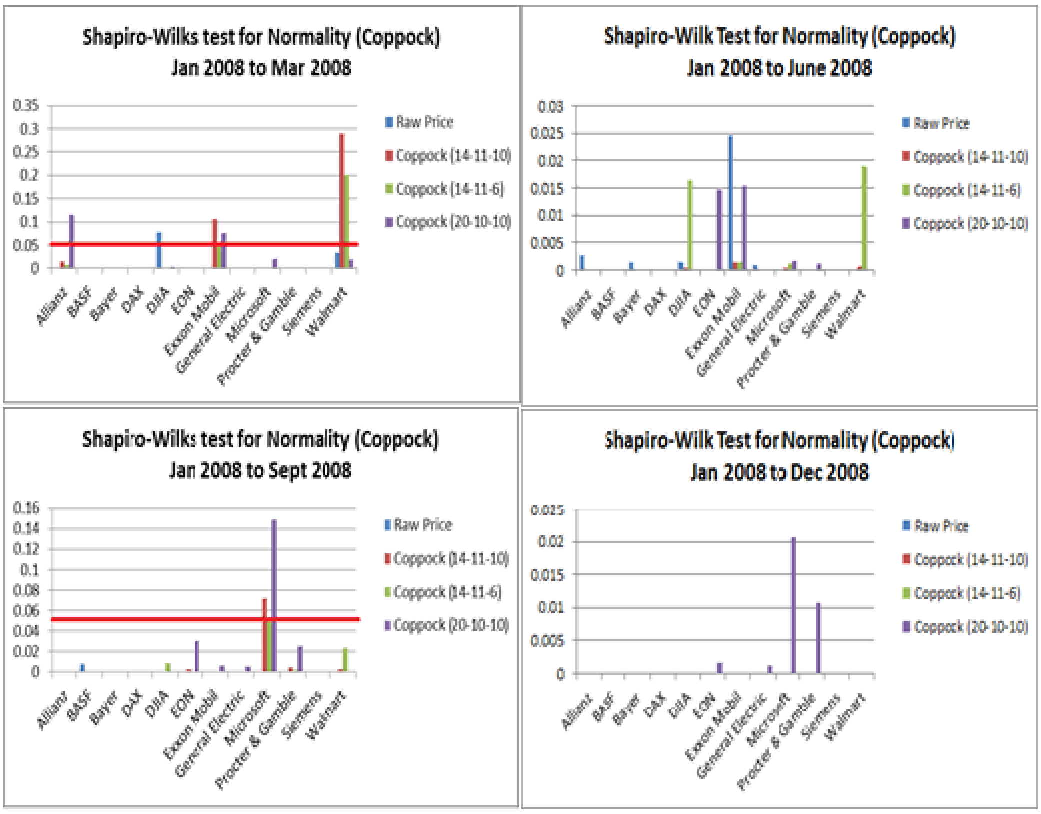

Figure 5.3: Shapiro-Wilk test for normality on the raw financial prices and derived Coppock values – 2008.

For each of the time frames in 2008, the Shapiro-Wilk normality test applied against the financial price data yields more occurrences where the results exceed the alpha value of 0.05. Very few raw prices are of normal Gaussian distribution, but, when the Coppock Values are derived using the different parameter sets (14-11-10, 14-11-6, 20-10-10), this yields more occurrences which exceed the alpha threshold of 0.05. These entries which exceed the 0.05 threshold pass the Shapiro-Wilk test, and are considered suitable to be used in the Pearson correlation check, as long as the corresponding data set is also considered to be of a normal distribution.

5.1.4 Shapiro-Wilk test for normalisation on stock price data – 2014

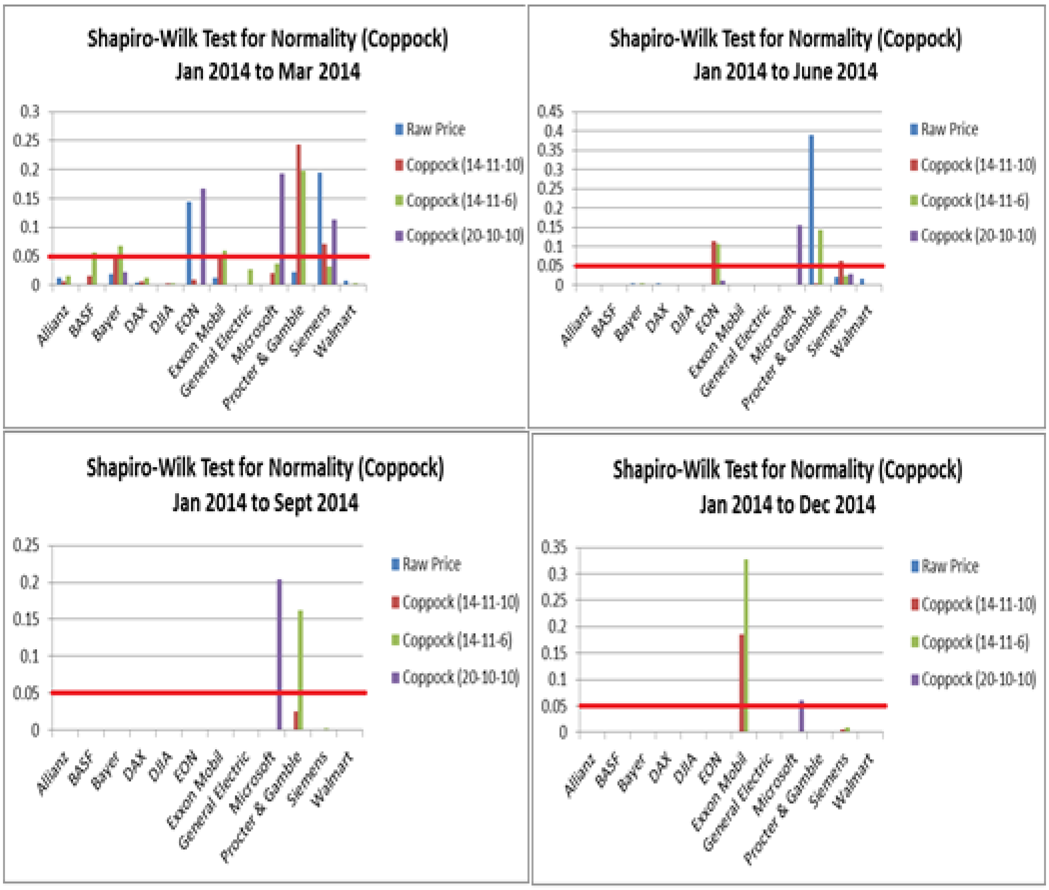

Figure 5.4: Shapiro-Wilk test for normality on the raw financial prices and derived Coppock values – 2008.

(Threshold of 0.05 represented by horizontal red line.)

In 2014, initially for the first three-month period, there are a high number of occurrences which pass the Shaprio-Wilk normality test. This, again, is achieved through the calculation of the Coppock values using the three different parameter sets (14-11-10, 14-11-6 or 20-10-10). As each period is extended, there is a reduction in the number of occurrences where the alpha value of 0.05 is exceeded.

One condition required in order to perform a Pearson correlation check requires that both datasets are of a normal (Gaussian) distribution. Despite the fact that there were individual occurrences of data passing the Shapiro-Wilk normality test, when these results (Wikipedia and financial) were combined, the net result of those datasets being normally distributed was reduced. Appendix A contains the complete Shaprio-Wilk results, and also indicates those companies and/or indexes where both Wikipedia data and financial data were normally distributed. Table 5.1, below, summarises the stocks and/or indexes where both Wikipedia data and financial data are both normal, and thus can have the Pearson correlation check run against them. Due to the low occurrence of instances where both dataset are normally distributed, the Spearman rank order correlation check will be applied for all datasets. As part of this research, for the instances where both datasets are normally distributed, the Pearson correlation check will be completed to determine whether any correlation improvement is returned when compared to their corresponding Spearman correlation results.

2008								
3 month data set - January 2008 to March 2008 - Shapiro-Wilk Results								
Company	Raw Wiki	Log10 Wiki	SROC Wiki		Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Exxon Mobil	0.00	0.39	0.00		0.00	0.11	0.06	0.08
Walmart	0.00	0.26	0.00		0.03	0.29	0.20	0.02
2014								
3 month data set - January to March 2014 - Shapiro-Wilk Results								
Company	Raw Wiki	Log10 Wiki	SROC Wiki		Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
BASF	0.00	0.00	0.09		0.00	0.02	0.06	0.00
Bayer	0.09	0.11	0.00		0.02	0.05	0.07	0.02
Exxon Mobil	0.05	0.01	0.60		0.01	0.05	0.06	0.00

Table 5.1: Datasets where both results are of normal distribution, indicating Pearson correlation suitability – 2008/2014.

Correlation checks

Following the completion of the Shaprio-Wilk test, the Spearman correlation test was chosen, and was performed for each of the time frames mentioned. Each table outlines the best correlation achieved, along with the data transformation performed (if applicable) on either/both of the datasets in question. The tables are split into stock market index and associated shares, and sorted by correlation strength. A breakdown of each stock market index (DAX and DJIA), along with the associated stock, will be presented. Each will give the results of the Spearman rank order correlation tests for the three-, six-, nine- and 12-month period for each year, 2008 and 2014. A stock market commentary will be initially presented for each stock market index/year. This will place the "mood" of the market at the time into perspective, and will assist in understanding the behaviour of the data and associated correlations produced.

5.1.5 Correlation Results – 2008 - German DAX index and shares.

January to March 2008			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DAX Index	SROC Wiki/Coppock(20_10_10)	-0.83	0.83
BASF	SROC Wiki/Coppock(14_11_06)	-0.48	0.48
Allianz	SROC Wiki/Coppock(20_10_10)	-0.38	0.38
Bayer	SROC Wiki/Coppock(14_11_06)	-0.35	0.35
Siemens	SROC Wiki/Coppock(20_10_10)	-0.15	0.15
EON	SROC Wiki/Coppock(20_10_10)	0.21	0.21
		Average Strength:-	**0.40**

January to June 2008			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DAX Index	SROC Wiki/Coppock(20_10_10)	-0.74	0.74
Bayer	SROC Wiki/Coppock(14_11_06)	-0.58	0.58
EON	SROC Wiki/Coppock(20_10_10)	0.35	0.35
Allianz	SROC Wiki/Coppock(14_11_06)	-0.24	0.24
BASF	Raw Wiki/Coppock(20_10_10)	0.21	0.21
Siemens	Raw Wiki/Coppock(20_10_10)	0.19	0.19
		Average Strength:-	**0.39**

January to September 2008			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DAX Index	SROC Wiki/Coppock(20_10_10)	-0.69	0.69
Bayer	SROC Wiki/Coppock(20_10_10)	-0.37	0.37
Allianz	SROC Wiki/Coppock(14_11_06)	-0.28	0.28
EON	SROC Wiki/Coppock(20_10_10)	0.28	0.28
Siemens	SROC Wiki/Coppock(20_10_10)	-0.23	0.23
BASF	SROC Wiki/Coppock(14_11_06)	-0.15	0.15
		Average Strength:-	**0.33**

January to December 2008			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DAX Index	SROC Wiki/Coppock(20_10_10)	-0.63	0.63
Siemens	SROC Wiki/Coppock(20_10_10)	-0.45	0.45
BASF	SROC Wiki/Coppock(14_11_06)	-0.31	0.31
Bayer	SROC Wiki/Coppock(20_10_10)	-0.29	0.29
Allianz	Raw Wiki/Coppock(20_10_10)	-0.23	0.23
EON	SROC Wiki/Coppock(20_10_10)	0.12	0.12
		Average Strength:-	**0.34**

Table 5.2: Correlation results for 2008 on DAX index and associated shares (ordered by strength).

Stock market commentary – DAX – 2008

As can be seen in Figure 5.5, below, the DAX market had a bearish (downward) trend, with a significant decline following the collapse of Lehman Brothers on 15th September, 2008. Following this rapid decline, a period of sideways movement formed into the end of the year. It is during this period of decline, especially after the collapse of Lehman, that a heightened state of fear existed in the market, leading to the need for information through various online media, including Wikipedia.

Figure 5.5: Graph of German DAX index – 1st January, 2008 to 31st December, 2008 (Yahoo Finance).

Three-month Correlation Window (January, 2008 to March, 2008)

As can be seen in Table 5.3, the optimum correlation was obtained by the DAX index. This was achieved through the recommended use of the 20 rate of change (ROC)/10 rate of change (ROC)/10 weighted moving average (WMA) Coppock calculation parameters. Each of the Coppock values for the DAX entry correlated optimally with the transformed Wikipedia data, which used the recommended Smoothed rate of change (SROC) calculation. Using these momentum calculations, this removed the unnecessary noise from the data, and thus achieved more distinctive signals, through which the better correlations were determined.

Other correlations were also achieved through the recommended alternative set of Coppock calculation parameters (14 ROC/11 ROC/6 WMA). Using one of these parameters to generate the Coppock values creates faster signals than the original monthly parameters (14 ROC/11 TOC/10 WMA). Because the data is daily, this proves to be effective in creating a better correlation between both datasets. Four out of the six entries use the 20/10/10 parameters. For each of the other entries, the correlations are not as strong as the highest achieved by the DAX index entry, but there is an improvement in correlation strength using the momentum calculations (Coppock and SROC Wiki) than would be achieved through the use of the raw data on its own (raw price/raw Wiki). It should be noted that none of these optimum correlations were achieved using the standard Coppock monthly parameters (14 ROC/11 ROC/10 WMA), and, therefore, this affirms the information gathered during the literature review[14] to use the recommendation parameters on daily data (20 ROC/10 ROC/10 WMA or 14 ROC/11 ROC/6 WMA). These parameters used to derive the Coppock values, combined with the Smoothed rate of change of the Wikipedia data, achieved the best correlations.

Six-month correlation window (January, 2008 to June, 2008)

The DAX index achieved the best optimum correlation, with strength of -0.74. This indicates that the SROC Wikipedia data is negatively correlated with the Coppock data. This optimum correlation was below the equivalent on the three-month window, which indicates that more data does not add value. The 20 ROC/10ROC/10WMA parameters used for the generation of the Coppock Values achieved this optimum correlation and match the parameters used to achieve the equivalent three-month correlation. The "Bayer" and "EON" stocks increased in correlation strengths using the same Wiki and Coppock parameters. EON increased in correlation strength, resulting in a stronger positive correlation than was achieved in the three-month period.

[14] "Using the Coppock Curve to Generate Stock Trade Signals [Online]. Available: http://www.investopedia.com/articles/active-trading/031814/using-coppock-curve-generate-stock-trade-signals.asp [Accessed 15 December 2014]."

As an example, the EON stock had a medium positive correlation (0.35). This indicates that, as the share price either dropped or increased, there was also an associated drop or increase in the Wikipedia views, but not directly due to a small strength of association which displayed the share price and associated Wikipedia views. Screenshots of Wikipedia Article Traffic Statistics can be review in more detail in Appendix A. In particular, there was a small strength of correlation where the EON share price rose, with the associated Wikipedia view also rising. Towards the end of June, there was a drop in share price, which was matched with an associated drop in Wikipedia page views. In order to achieve the optimum correlations for the "BASF" and "Siemens" stocks, the raw Wiki data was correlated against the Coppock values (20ROC/10ROC/10WMA), which differed from the same set in the three-month period.

Nine-month correlation window (January, 2008 to September, 2008)

The DAX index achieved the optimum correlation strength, although it decreased from both of the previous three- and six-month time frames. In all cases, the transformed Wiki data (SROC) was used to achieve optimal correlations. All entries remained negatively correlated, except for EON, similar to the prior periods, where there was a positive correlation but a reduction from the prior six-month period. All entries used the recommended Coppock calculation parameters of either 20ROC/10ROC/10WMA or 14ROC/11ROC/6WMA.

12-month correlation window (January, 2008 to December, 2008)

The DAX remained the best correlated pair, with a negative strength of -0.63. This remained in the large strength of association. The strength rank order of each of the other stocks changed when compared to the prior nine-month period, with Siemens and BASF almost doubling in correlation strength, while the other stocks (Bayer, Allianz and EON) reduced further in correlation. Therefore, for the longest time window, the DAX index remained the entry with the largest strength association, and remained consistently so throughout all periods.

Summary

The DAX index consistently returned the best correlation strength for each of the four periods being analysed in 2008. These strengths were negatively correlated, which indicates that, as prices decrease, Wikipedia page views increase, and vice versa. This optimum strength was achieved in the shorter, three-month period but remained strong through the year. When the number of page views was assessed for the full year 2008, the DAX was one of the most viewed pages of the companies being analysed. EON received the least number of page views over the one year period. The associated correlative strength for EON remained weak, which would indicate that a higher page view was required to gain stronger correlation. The Average strength in correlation remained in the same range throughout the year, indicating a fear or concern in the online community.

Share/Index	No. of Page Views
Bayer	232173
DAX Index	196060
BASF	174935
Siemens	162667
Allianz	135083
EON	72831

Table 5.3: Number of Wikipedia page views on the DAX market and associated shares in 2008.

5.1.6 Correlation Results – 2008 - DJIA index and shares.

January to March 2008			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
Procter and Gamble	SROC Wiki/Coppock(14_11_06)	-0.91	0.91
Walmart	SROC Wiki/Coppock(20_10_10)	0.62	0.62
General Electric	SROC Wiki/Coppock(20_10_10)	-0.52	0.52
Microsoft	SROC Wiki/Coppock(14_11_10)	-0.49	0.49
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.39	0.39
Exxon Mobil	Raw Wiki/Coppock(14_11_06)	0.39	0.39
		Average Strength:-	**0.55**

January to June 2008			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
General Electric	SROC Wiki/Coppock(20_10_10)	-0.53	0.53
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.50	0.50
Microsoft	SROC Wiki/Coppock(14_11_06)	-0.47	0.47
Procter and Gamble	SROC Wiki/Coppock(14_11_06)	-0.45	0.45
Exxon Mobil	SROC Wiki/Coppock(20_10_10)	-0.28	0.28
Walmart	SROC Wiki/Coppock(14_11_06)	-0.21	0.21
		Average Strength:-	**0.41**

January to September 2008			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
General Electric	SROC Wiki/Coppock(20_10_10)	-0.57	0.57
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.56	0.56
Procter and Gamble	SROC Wiki/Coppock(14_11_10)	-0.50	0.50
Microsoft	SROC Wiki/Coppock(14_11_06)	-0.33	0.33
Walmart	SROC Wiki/Coppock(14_11_10)	-0.25	0.25
Exxon Mobil	Raw Wiki/Coppock(14_11_06)	0.18	0.18
		Average Strength:-	**0.40**

January to December 2008			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.52	0.52
General Electric	SROC Wiki/Coppock(20_10_10)	-0.44	0.44
Procter and Gamble	SROC Wiki/Coppock(14_11_06)	-0.29	0.29
Walmart	SROC Wiki/Coppock(14_11_06)	-0.22	0.22
Microsoft	SROC Wiki/Coppock(14_11_10)	-0.21	0.21
Exxon Mobil	SROC Wiki/Coppock(20_10_10)	-0.13	0.13
		Average Strength:-	**0.30**

Table 5.4: Correlation results for 2008 on DJIA Index and associated shares (ordered by strength).

Stock market commentary – DJIA – 2008

As can be seen in Figure 5.2, below, similarly to the DAX index for 2008, there was a bearish trend (decline) in the DJIA index throughout the year, with a significant decline following the collapse of Lehman Brothers on 15th September, 2008 (indicated by crosshairs in the chart). Following the rapid decline in the latter quarter of the year, there was a period of relative calm as the market became range-bound between 8000 and 9000, although the swings from positive to negative and vice versa in the final quarter were quite extreme, indicating that fear remained in the market.

Figure 5.6: Graph of German DJIA index – 1st January, 2008 to 31st December 2008 (Yahoo Finance).

Three-month correlation window (January, 2008 to March, 2008)

The strongest correlation was achieved by Procter and Gamble, where there was a negative correlation of -0.91. This is considered a very large strength of association, and used the transformed Wikipedia data (SROC), in addition to the Coppock values derived using the 14ROC/11ROC/6WMA parameters. This high correlation was achieved due to the fact that it was the smaller set of values on which to perform correlation checks. This indicated that, as the Coppock curve (price) turned negative, there was an increase in the number of Wikipedia page viewings. In Figure 5.3, for Procter and Gamble, the Wiki and Coppock results can be compared, revealing that, as the Wiki SROC turned down, the Share Price/Coppock Curve turned up.

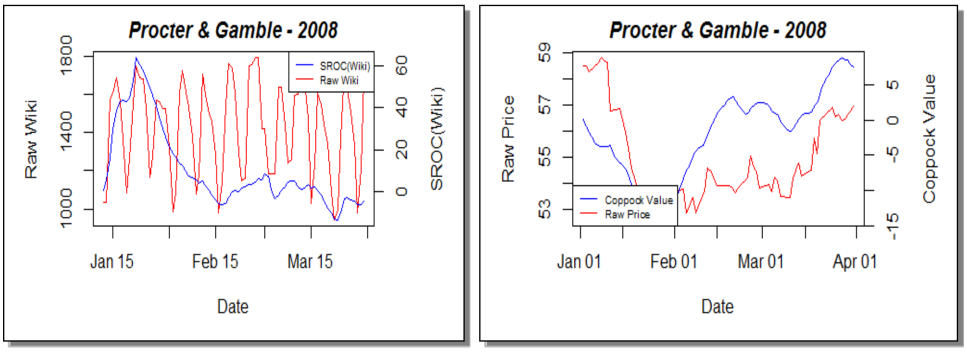

Figure 5.7: Graphs representing the Wiki (SROC) versus Coppock value for P&G – raw data in red, derived data in blue.

Conversely, as the Coppock curve (price) turned positive; there was a decrease in the Wikipedia page views. Walmart returned a positive correlation with a large strength of association (0.62), indicating that, for an increase in the Coppock curve, there is a relative increase in the SROC Wiki line, and visa-versa. This would also indicate that there is an increase in the associated Wikipedia page as the price increases or decreases. General Electric, Microsoft and the DJIA index revealed a negative correlation between their Wikipedia page views and associated Coppock value. This, again, would indicate that there was a general increase in page views as the prices decreased, and visa-versa. Exxon Mobil, similarly to Walmart in the same category, revealed a positive correlation which had a medium strength of association (0.39).

Six-month correlation window (January, 2008 to June, 2008)

General Electric maintained the same correlation strength as achieved in the previous month, accomplishing the strongest correlation strength in the time range. All other stocks achieved a negative correlation using both the derived Wikipedia values (SROC) and associated Coppock value. Similarly to other data ranges, all Coppock values were derived using either the 20ROC/10ROC/10WMA parameters or

14ROC/10ROC/6WMA parameters. This also indicates that, as prices decrease over a period, there is an increase in Wikipedia page views.

Nine-month correlation window (January, 2008 to September, 2008)

There was a slight increase in correlation (negative) on General Electric which indicates that, while the financial crisis took hold in September, 2008, with prices decreasing, there was a gradual increase in associated Wikipedia page views. Similarly, there was an increase in negative correlation between the DJIA index prices (Coppock) and the associated Wikipedia page views. This also indicates that there was awareness and concern as the index dropped in value, thus revealing an increase in associated Wikipedia page views.

12-month correlation window (January, 2008 to December, 2008)

This window of time included the period when the DJIA Index was soon to reach its low of 7062, in February, 2009. Thus, there was concern within the community over the state of the financial markets. As a consequence, there was a higher likelihood of people having an interest in the markets, in this case the Dow Jones Industrial Average. This was affirmed by fact that the DJIA index achieved the largest correlation strength among the set of shares being analysed. This negative correlation using the SROC Wiki and Coppock value (-0.52), deemed to be of a medium strength of association, indicates that, as the index value decreased, there was an increase in the associated Wikipedia page views, most likely indicating the influence of people’s concern. Similarly, there were negative correlations, of medium and small strength, which would indicate an interest in the Wikipedia pages as the prices decreased in value, although not as strongly correlated as the DJIA index.

Summary

Relative to the stock market performance of the Dow Jones Industrial Average, the majority of correlations were reflective of the stock market for each period. For the first quarter, there was relative calm in the market; however, midway during the second quarter, there was an increase in correlation strength on the major index (DJIA) and General Electric. Over the third quarter of 2008, there was a rapid drop in the stock market and associated shares. This concern was reflected in the increase of strength in (negative) correlation, again on the DJIA index and General Electric. Towards the end of the year, when the market appears to have bottomed out for 2008, the fear subsided in the market, and the corresponding strengths in correlation also reduce slightly. As shown in Table 5.5 below, the DJIA index and General Electric were among the most highly viewed pages on Wikipedia, and thus would be more representative of the market over the period.

Share/Index	No. of Page Views
Microsoft	3843957
DJIA Index	1716478
General Electric	874634
Procter and Gamble	512655
Walmart	404697
Exxon Mobil	363262

Table 5.5: Number of Wikipedia page views on DJIA market and associated shares in 2008.

5.1.7 Correlation Results – 2014 - German DAX index and shares.

January to March 2014			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
Bayer	SROC Wiki/Coppock(20_10_10)	-0.47	0.47
DAX Index	SROC Wiki/Coppock(20_10_10)	-0.47	0.47
BASF	SROC Wiki/Coppock(14_11_06)	0.29	0.29
EON	SROC Wiki/Coppock(20_10_10)	-0.28	0.28
Siemens	SROC Wiki/Coppock(20_10_10)	-0.24	0.24
Allianz	SROC Wiki/Coppock(20_10_10)	-0.17	0.17
		Average Strength:-	**0.32**

January to June 2014			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
Siemens	SROC Wiki/Coppock(20_10_10)	-0.23	0.23
EON	SROC Wiki/Coppock(20_10_10)	-0.22	0.22
Bayer	SROC Wiki/Coppock(20_10_10)	-0.18	0.18
DAX Index	SROC Wiki/Coppock(14_11_10)	-0.18	0.18
BASF	SROC Wiki/Coppock(20_10_10)	-0.16	0.16
Allianz	SROC Wiki/Coppock(14_11_10)	-0.13	0.13
		Average Strength:-	**0.18**

January to September 2014			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DAX Index	SROC Wiki/Coppock(20_10_10)	-0.33	0.33
EON	SROC Wiki/Coppock(20_10_10)	-0.23	0.23
BASF	Raw Wiki/Coppock(14_11_10)	0.10	0.10
Siemens	SROC Wiki/Coppock(20_10_10)	-0.09	0.09
Allianz	Raw Wiki/Coppock(20_10_10)	-0.06	0.06
Bayer	Raw Wiki/Coppock(14_11_10)	0.03	0.03
		Average Strength:-	**0.14**

January to December 2014			
DAX Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DAX Index	SROC Wiki/Coppock(14_11_10)	-0.34	0.34
Allianz	SROC Wiki/Coppock(14_11_06)	-0.12	0.12
Bayer	SROC Wiki/Coppock(20_10_10)	-0.11	0.11
BASF	Raw Wiki/Coppock(20_10_10)	0.08	0.08
EON	SROC Wiki/Coppock(14_11_06)	-0.07	0.07
Siemens	SROC Wiki/Coppock(20_10_10)	0.04	0.04
		Average Strength:-	**0.13**

Table 5.6: Correlation results for 2014 on DJIA index and associated shares (ordered by strength).

Stock market commentary – DAX – 2014

As can be seen in Figure 5.3, below, the market was relatively range-bound for the year, after having made a large recovery following the financial crisis of 2008. There was high volatility experienced within the range mentioned, causing sudden declines, followed by a period of rapid recovery. This would indicate that there was still uncertainty in the market which was prone to sudden corrections, followed by a swift recovery of confidence.

Figure 5.8: Graph of German DAX index – 1st January, 2014 to 31st December, 2014 (Yahoo Finance).

Three-month correlation window (January, 2014 to March, 2014)

Both the DAX index and Bayer stock highlighted a negative correlation, with a medium strength of association. All optimal correlations were achieved through the use of the derived Wikipedia data using the Smoothed rate of change and the Coppock value, involving the 20ROC/10ROC/10WMA parameters in all cases except BASF, which used the 14ROC/11ROC/6WMA parameters, resulting in a positive correlation of 0.29.

Six-month correlation window (January, 2014 to June, 2014)

There was a decline in correlations across all shares and indexes when compared to the previous time frame. This, it can be understood, occurred as the stock market experienced a period of growth in the second quarter. This would have resulted in reduced concern amongst the community. All optimal correlation strengths were achieved through the use of the transformed Wikipedia data using the Smoothed rate of change and the Coppock value, via a combination of 20ROC/10ROC/10WMA and 14ROC/11ROC/10WMA. The highest correlations in the previous period (Bayer and

DAX) lost a large amount of correlation strength over this period. Through chart analysis of Figure 5.3, there is clearly an upward trend in the market over the latter part of this six-month time frame. Due to the fact that there appeared to be a strong negative correlation between Wikipedia SROC and Coppock values during the stock market decline, the fact that the market was increasing over this period could explain why there was a sudden decrease in correlation – there were less Wikipedia page views due to newfound confidence in the market over this period. The average strength almost halved in value between the three-month period and the six-month period.

Nine-month correlation window (January, 2014 to September, 2014)

The DAX Index continued to have the best correlation using the derived Wiki data (SROC) and the Coppock values (20ROC/10ROC/10WMA). This is almost a 50% increase in correlation since the prior period. Considering the market at the time, there was a large sell-off on the DAX exchange up to August, 2014, which would have increased concern in the market and the wider arena. This would have caused an increase in Wikipedia page views over that period, thus causing an increase in negative correlation (as the exchange value falls, the Wikipedia page view increases). EON maintained almost the same correlation strength. Interestingly, BASF changed to a positive correlation from its prior period negative correlation. This would indicate that, as the market declines, there is more of a tendency for the Wikipedia viewership to decline also, although this correlation is deemed weak (0.10). There was a decrease in correlation strength for Siemens, Allianz and Bayer, to close to zero, thus indicating no correlation between their Wikipedia page views (SROC) and corresponding Coppock values.

12-month correlation window (January, 2014 to December, 2014)

The DAX exchange experienced the highest volatility over the latter quarter of 2014, with large sell-offs occurring, followed by a rapid recovery. This would indicate that there was a large element of fear in the market. This may explain why the DAX index correlation strength between Wikipedia views (SROC) and associated Coppock curve (14ROC/11ROC/10WMA) maintained the negative correlation strength of -0.34. Normally, over the 12-month period, there is a decline in correlation strength compared to earlier shorter periods; however, in this case, the DAX index correlation increased slightly. This would indicate that there was fear/concern in the community. With a medium strength of association (negative correlation), this indicates that, as prices dropped, there was an increase in Wikipedia page views. All other shares returned a small strength of association between their Wiki viewership and associated Coppock curve.

Summary

The majority of optimum correlations were achieved through the use of Wiki (SROC) and Coppock values, of which most were derived using the 20/20/10 ROC and WMA parameters. During periods of heightened fear on the market when there is a rapid decline (e.g. the last quarter of 2014), there is an increase in correlation strength on the DAX index. This would support the assertion that there is an increase in online research during periods of fear/downturn in the market. On analysing the page views for 2014, there is an increase in Wikipedia page views for all stock except the DAX, when compared to equivalent page views in 2008. For the DAX page views, this would indicate, due to relative market calming in 2014 compared to 2008, that there was less concern in the market, and therefore a lesser need in the community to research further.

Share/Index	No. of Page Views
Siemens	513874
Bayer	314427
BASF	280177
Allianz	213870
DAX Index	152449
EON	133056

Table 5.7: Number of Wikipedia page views on DAX market and associated shares in 2014.

5.1.8 Correlation Results – 2014 - DJIA index and shares.

January to March 2014			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.83	0.83
General Electric	SROC Wiki/Coppock(20_10_10)	-0.78	0.78
Walmart	SROC Wiki/Coppock(20_10_10)	-0.70	0.70
Exxon Mobil	SROC Wiki/Coppock(20_10_10)	-0.56	0.56
Microsoft	SROC Wiki/Coppock(20_10_10)	-0.31	0.31
Procter and Gamble	Raw Wiki/Coppock(20_10_10)	0.16	0.16
		Average Strength:-	**0.56**
January to June 2014			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.53	0.53
General Electric	SROC Wiki/Coppock(20_10_10)	-0.34	0.34
Exxon Mobil	SROC Wiki/Coppock(20_10_10)	-0.30	0.30
Procter and Gamble	SROC Wiki/Coppock(14_11_10)	-0.30	0.30
Microsoft	SROC Wiki/Coppock(14_11_10)	-0.25	0.25
Walmart	SROC Wiki/Coppock(20_10_10)	-0.21	0.21
		Average Strength:-	**0.32**
January to September 2014			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
Exxon Mobil	SROC Wiki/Coppock(20_10_10)	-0.48	0.48
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.30	0.30
General Electric	SROC Wiki/Coppock(20_10_10)	-0.25	0.25
Walmart	SROC Wiki/Coppock(14_11_06)	-0.17	0.17
Procter and Gamble	SROC Wiki/Coppock(20_10_10)	-0.13	0.13
Microsoft	SROC Wiki/Coppock(20_10_10)	0.10	0.10
		Average Strength:-	**0.24**
January to December 2014			
DJIA Index and Shares	**Optimum Correlation Pair**	**Correlation Strength**	**Absolute**
DJIA Index	SROC Wiki/Coppock(20_10_10)	-0.46	0.46
Exxon Mobil	SROC Wiki/Coppock(20_10_10)	-0.22	0.22
General Electric	SROC Wiki/Coppock(20_10_10)	-0.18	0.18
Procter and Gamble	SROC Wiki/Coppock(20_10_10)	-0.12	0.12
Microsoft	SROC Wiki/Coppock(14_11_06)	0.07	0.07
Walmart	Raw Wiki/Coppock(20_10_10)	0.20	0.20
		Average Strength:-	**0.21**

Table 5.8: Correlation results for 2014 on DJIA index and associated shares (ordered by strength).

Stock market commentary – DJIA – 2014

There was an obvious bullish trend in the market over the full year. This also consisted of sudden corrections throughout the year, followed by rapid recovery after each correction. This would indicate that there was a well-established trend and confidence in the DJIA market. The periods of interest are those where there was high volatility, with declines followed by quick recovery.

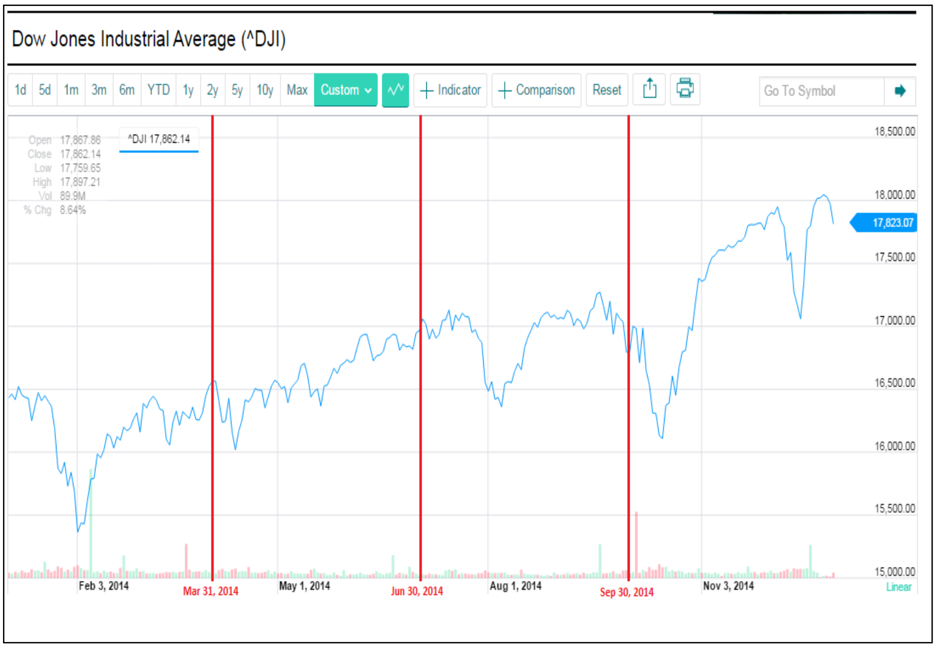

Figure 5.9: Graph of DJIA index – 1st January, 2014 to 31st December, 2014 (Yahoo Finance).

Three-month correlation window (January, 2014 to March, 2014)

There was a high period of decline on the stock market during this period, with a rapid recovery following this decline. The Dow Jones index correlation proved to be the strongest over this period, with a negative correlation strength of -0.83. This is regarded as a large strength of correlation, which indicates that, as the market decreases there is an increase in the associated Wikipedia page views, and vice versa. General Electric, Walmart and Exxon Mobil, during this period, also reflect a large strength of correlation, with Microsoft and Procter and Gamble showing medium and small strengths of correlation, respectively. All correlations for each stock, except one (Procter and Gamble), used the same correlation pairs (SROC Wiki and Coppock

20/10/10). Due to the high volatility of the market, it is clear that the Wikipedia views increased as the index decreased.

Six-month correlation window (January, 2014 to June, 2014)

The stock market recovered following the initial three-month period, and formed a bullish trend. Thus, there was less fear in the market towards the latter part of the six-month period. The correlation strengths per stock/index seem to reflect this, with a reduction in strength due to less fear in the market, and thus a lesser need to research online sources such as Wikipedia. All correlations used the transformed Wikipedia data (SROC), along with either the Coppock 20ROC/10ROC/10WMA or 14ROC/11ROC/10WMA values. The average correlation strength decreased by 42% between this time range and the previous three-month period. This can be explained by the increase in positive sentiment in the market over that period.

Nine-month correlation window (January, 2014 to September, 2014)

The stock market over the latter quarter (June to September) of this period experienced a pullback (correction), which would have instilled fear into the market. All shares/index correlations used the derived Wikipedia (SROC) and Coppock values (using 20ROC/10ROC/10ROC and 14ROC/11ROC/6 ROC). Exxon Mobil experienced an increase in correlation from the previous six-month time frame. This would indicate that, as the share price dropped for this share, there was an increase in page views for that period, thus improving the correlation. The Exxon Mobil Wikipedia page view figure for August, 2014 was 36,210. This increased to 50,441 page views in September, representing a percentage increase of 40% pages views between August and September. Figure 5.10 below, outlines the correlation of negative strength between the Wiki (SROC) and associated Coppock value.

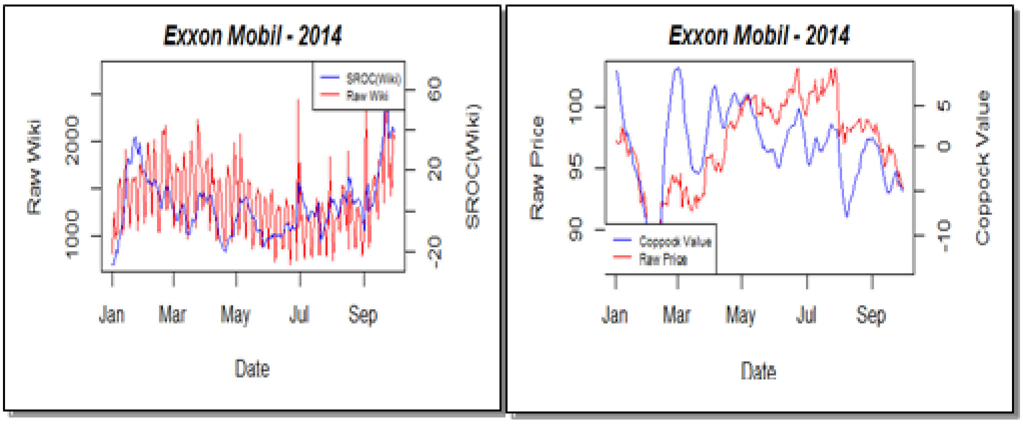

Figure 5.10: Graphs representing the Wiki (SROC) versus Coppock value for Exxon.

Microsoft moved from negative correlation to positive correlation, due to a spike in page views during the month, resulting in an increase in page views as the associated share price increased.

12-month correlation window (January, 2014 to December, 2014)

Towards the last quarter of 2014, the stock market experienced a sudden pullback (correction) followed by a quick recovery. This, again, would have instilled fear into the market, causing an increase in online research. The negative correlations for the DJIA index decreased to -0.46, thus giving it a medium strength of association. This indicates that, as the price decreased, there was an increase in Wikipedia page views. All stocks/index used the transformed Wikipedia data (SROC) and Coppock generation parameters (20ROC/10ROC/10WMA or 14ROC/11 ROC/6 WMA), except for Walmart, where the optimum correlation was achieved using the raw Wiki data against the Coppock values.

Summary

Table 5.9 outlines the number of Wikipedia page views over the 12-month period of 2014.

Share/Index	No. of Page Views
Microsoft	2744653
Walmart	1436857
General Electric	1263233
DJIA Index	800594
Procter and Gamble	752056
Exxon Mobil	528375

Table 5.9: Number of Wikipedia page views on Dow Jones Industrial Average and associated shares in 2014.

When compared to 2008, similarly to the comparison concerning the DAX index and associated shares, there was an increase in page views for the individual shares in 2014 when compared to 2008, but a decrease in page views on the index. This would indicate that the DJIA index Wikipedia page views served as a better barometer of the financial community and the concern factor associated with it. In 2008, during the beginning of the financial crisis, there was an elevated concern in the market which was highlighted by a high number of Wikipedia page views. Following a period of recovery, there was a relative reduction in concern in the market, represented by the reduction of Wikipedia page views in 2014.

5.2 Discussion

The aim of this research was to determine whether Wikipedia article traffic statistics can be used to confirm the signal provided by the Coppock indicator. Through the correlation checks between the Wikipedia article traffic statistics and the associated Coppock value, it is hoped that this confirmation can be achieved by technical analysts. Specifically, within the context of technical analysis, the objective of this research was to:

i. Determine the most suitable correlation technique by performing a normality check on each data set;
ii. Evaluate the correlations achieved between each dataset over the various time periods for each year in question;

iii. Assess the results from the correlations obtained and compare these to what was expected; and

iv. Propose recommendations for the use of Wikipedia article traffics statistics as confirmation of the signal given by the Coppock indicator.

This section will revisit the research objectives detailed above, and will summarise the findings and present conclusions.

Following the Shapiro-Wilk test for normality, and based on the work of Moat et al. (2013), the Spearman rank order correlation check was chosen to determine the relationship between Wikipedia article traffic statistics and the associated Coppock value. Elder (1993) has determined that, in order to obtain a significant signal from a time series, the Smoothed rate of change (SROC) can be used to achieve this. On that basis, the SROC was chosen as a method of obtaining a better signal from the Wikipedia article traffic statistics.

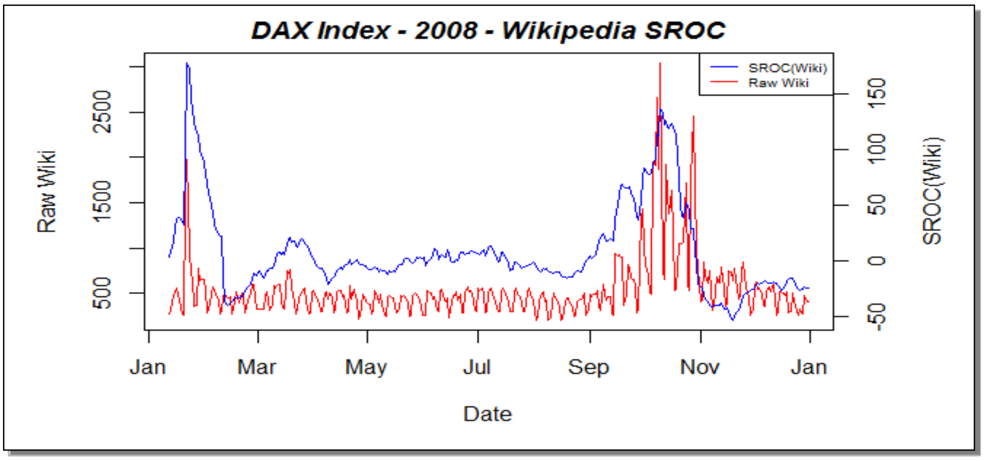

Figure 5.11: Smoothed Rate of Change applied to underlying DAX Wikipedia Page Views – 2008 Data.

As can be seen in Figure 5.11, a more significant set of signals is given by the derived SROC, which could correlate better with the associated Coppock curve. The original Coppock Curve was designed to run against monthly data using the following parameters:-

- 14-month Rate of Change.
- 11-month Rate of Change.
- 10-month Weighted Moving Average.

In order to obtain significant signals from the associated daily financial data, a number of recommended derivation parameters for the calculation of the Coppock curve were recommended[15]. These recommendations consisted of the following parameters:-

- 14-day Rate of Change.
- 11-day Rate of Change.
- 6-day Weighted Moving Average.

Or

- 20-day Rate of Change.
- 10-day Rate of Change.
- 10-day Weighted Moving Average.

As a result of using the recommended daily generation parameters, it resulted in the optimum correlation being achieved between the Wikipedia Dataset and associated Coppock Dataset where, the majority of optimum parameters used the 20ROC/10ROC/10WMA.

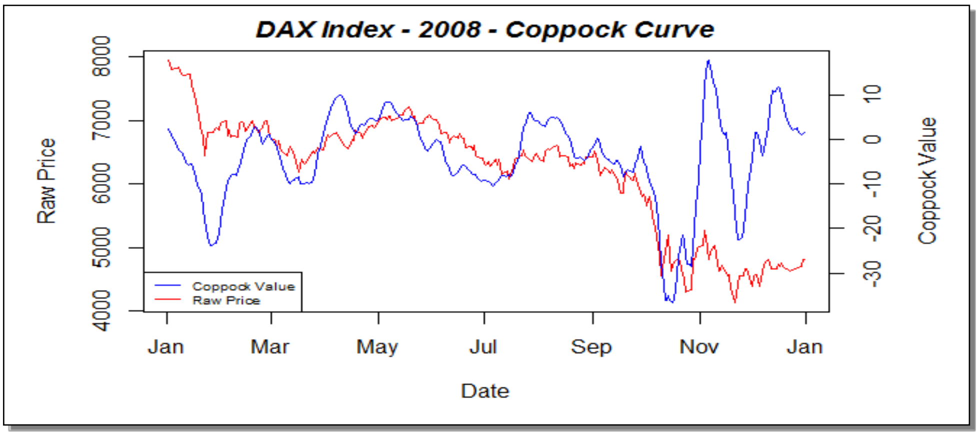

Figure 5.12: Coppock curve applied to underlying DAX index prices – 2008 data.

[15] "Using the Coppock Curve to Generate Stock Trade Signals [Online]. Available: http://www.investopedia.com/articles/active-trading/031814/using-coppock-curve-generate-stock-trade-signals.asp [Accessed 15 December 2014]."

Using these parameters, a set of Coppock values were obtained, and used to correlate against the associated Wikipedia SROC results. These achieved various strengths of correlation. The following are the key findings gained from this research exercise:

i. **Using SROC improves correlation with the Coppock curve**

In order to achieve an improvement in signal from data, Elder (1993) recommended the application of the Smoothed rate of change (SROC) against underlying data. This was applied to the Wikipedia page views, and resulted in improved correlations with the associated Coppock curve.

Stock / Index	Raw Wiki/Coppock	SROC/Coppock(14-11-6)	SROC/Coppock(14-11-10)	SROC/Coppock(20-10-10)
Allianz	-0.22	-0.05	-0.04	0.03
BASF	-0.11	-0.31	-0.29	-0.30
Bayer	-0.04	-0.25	-0.26	-0.29
DAX Index	-0.29	-0.54	-0.58	-0.63
DJIA	-0.29	-0.44	-0.47	-0.52
EON	0.06	0.08	0.11	0.12
Exxon Mobil	0.1	-0.06	-0.10	-0.13
General Electric	-0.24	-0.37	-0.40	-0.44
Microsoft	-0.07	-0.21	-0.21	-0.14
Procter and Gamble	-0.12	-0.29	-0.26	-0.17
Siemens	0.01	-0.34	-0.38	-0.45
Walmart	0.08	-0.22	-0.20	-0.20

Table 5.10: Comparison of raw Wiki correlation and SROC (Wiki) against Coppock values – best correlations in yellow.

As can be seen above, the correlation test using the Raw Wiki against Coppock only resulted in one optimum result. There was an improvement in correlation when the Smoothed rate of change was applied to the raw Wikipedia page view data. All occurrences except Allianz derived the best correlations from the SROC against the Coppock values.

ii. **Using recommended ROC/WMA parameters on Coppock calculation improves correlation.**

Using either the 14-day ROC/11-day ROC/6-day WMA or the 20-day ROC/10 day ROC/10-day WMA improves the Coppock signal for daily data, as recommended by Mitchell (2014) and StockCharts.com (2015). As can be seen in Table 5.10, 7 of the 12 stock/indexes using the (20/10/10) parameter set facilitated in achieving optimum correlation. Next to this, the recommended

(14/11/6) parameter set achieved 3 of the 12 optimum correlations. Therefore, in summary, 10 out of the 12 optimum correlations were achieved using the refined parameters suited to daily data.

iii. Majority of optimal correlations are negative.

In the majority of cases, when correlations were tested between the Wikipedia (SROC) and associated Coppock curve, a negative correlation was obtained. This indicated that, as the Coppock curve moved down (downward underlying share price movement), there was an increase in Wikipedia page views and as the share price or index increased, there was a reduction in Wikipedia Article Views. This confirmed the research conducted by Moat et al. (2013), which determined that a higher occurrence of online research through Wikipedia is conducted before periods of decline and continues as the decline progresses.

iv. Optimum correlation achieved in bear markets (downturn)

During the analysis of all periods in 2008 and 2014, it was notice that there were correlations of average higher strength in 2008, before and during the financial crisis, than the corresponding periods in 2014. This backup the research conducted by Moat et al. (2013) where they concluded that there are increases in Wikipedia traffic before a stock market fall. Also, these findings confirm the research done by Tversky and Kahneman (1991), where they conclude that losses and disadvantage has a greater impact on decision than gains and advantage. This is reflected during the comparison of the average strengths between Tables 5.2 and 5.6 (DAX Index and shares) and between Table 5.4 and 5.8 (DJIA Index and shares) where the average strengths in 2008 are stronger than their equivalents in 2014.

v. DAX Index and DJIA Index best capture the mood of the market.

On analysis of the correlations achieved in 2008 and 2014, the most consistent correlations are achieved by the DAX and DJIA Index over each of the timeframes and are most reflective of the stock market during these periods. This backs up the case made by Surowiecki (2004) which implies that there is inherent value in the Wisdom of Crowds. Each individual share generally reflects the specific interest in that holding, while interest in the DAX and DJIA attracts more of a general “crowd” audience, thus producing a higher, more consistent strength in correlation over all periods and timeframes.

vi. Correlations affirm certain stocks are better barometers of the market.

There are close ranking of strengths in correlation between the DJIA and General Electric during 2008 and 2014. This affirms the point made by Chambers (2000) that certain stocks are better barometers of the market. General Electric would be one of these, as it is only share of the original 12 to remain in the index since the index was formed in 1896. It can be seen in Table 5.4 for 2008 and Table 5.8 for 2014 that the correlation of General Electric are the closest to the DJIA index than any of the other chosen stocks.

6. CONCLUSIONS AND FUTURE WORK

This chapter revisits the objectives of this research. The key findings that were discovered during the exercise are described, and conclusions are presented. Areas of further research are discussed, specifically in relation to this research topic. Finally, the contribution of this research is also explained.

6.1 Problem definition and research overview

The objective of this research study was to determine whether the signal given by the Coppock indicator on a particular stock or index can be confirmed through the use of associated Wikipedia article traffic statistics. Specifically, within the area of technical analysis, the objectives of this research were to:

i. Determine a suitable correlation technique through the use of a suitable normality check.

ii. Determine the best rate of change (ROC) and weighted moving average (WMA) values to use in order to derive the optimal Coppock value.

iii. Apply the recommended Smoothed rate of change (SROC) against the Wikipedia data, in order to improve the correlation potential between the two datasets.

iv. Critically assess the correlations achieved through the use of the most applicable correlation technique.

v. Propose further research for the improvement of signals given by the Coppock indicator through the use of Wikipedia Article Traffic Statistics.

The goal of every investor is to be able to optimally time the entry and exit of a traded position on the stock market, in order to yield a profitable return. This can be achieved through the proper use of technical indicators. These indicators give a signal to an investor as to when a market or position may be over-bought or over-sold. Improved profits can be achieved by the investor through the disciplined use of these indicators.

The Coppock indicator is considered to be an indicator that has a reliable track record, and which can yield the investor a decent return (Gillen 2013). Originally designed to give a “buy” signal on monthly data, the Coppock indicator can also be used by investors to give a “sell” signal, and also functions over more frequent time frames, such as weekly and daily data (Mitchell 2014). Depending on the rate of change (ROC) and weighted moving average (WMA) parameters used to calculate the Coppock value, different entry and exit positions are returned by the Coppock curve. Two sets of parameters are regarded as offering the best Coppock signal on daily data. These consist of the application of the six-day weighted moving average on the product of the 14-day and 10-day rate of change, or the application of the 10-day weighted moving average on the product of the 20-day rate of change and 10-day rate of change. It was discovered that the latter (20, 10, 10) derived the optimal Coppock values that returned the optimal correlation with the Wikipedia article traffic statistics

Wikipedia is frequently used by the online community as a first point of reference, in order to research and understand a specific topic, stock market or company. Through the use of the underlying Wikipedia article traffic statistics, it is possible to build a profile of page views on any Wikipedia page over any period of time since 10th December, 2007. Through the use of these recorded Wikipedia statistics, it is also possible to determine whether there is any strength in correlation between Wikipedia page view traffic on a particular quoted company or stock market index and the associated Coppock values for that same company or index.

Four window sizes (three, six, nine and 12 months) were chosen for applying the correlation techniques. Initially, the strongest correlations were derived in the three-month window, which reduced in strength as the period was increased. It was also noticed that the strength in correlation remained high relative to each previous time frame when there was a general downturn in the stock market. This supports the assertion by Moat et al. (2013) that there was an increased tendency to research when there was a risk or fear of incurring a loss. It was also discovered that there were increased strengths in correlation for stock that were deemed to be barometers of the stock market. An example of this is General Motors (GM), which has been a member of the Dow Jones index since the inception of the exchange in 1896 (Nicholson 2010), and whose correlation strength of associations were similar to the overall Dow Jones index.

6.2 Contributions to body of knowledge

This dissertation focused on the Coppock indicator, and how Wikipedia article view statistics can affirm the signal provided by the Coppock indicator. By obtaining this confirmation, investors in stocks and shares can gain extra confidence that the signal given by the Coppock indicator is valid, and can apply this extra Wikipedia correlation signal to their investment strategy. To the best of the author's knowledge, no other piece of research uses Wikipedia article traffic statistics to verify a stock market technical indicator such as the Coppock indicator. This dissertation offers a contribution to the use of Spearman's rank order correlation to determine the strength of association between two datasets, and, from this, determining whether a stock market technical indicator is signally correctly.

6.3 Experimentation, evaluation and limitations

The experimentation required that the data was in a suitable state in order to uncover optimal correlations. This involved the resolution of missing data through the use of alternative sources. Also, there were issues of incompatibility due to the nonexistence of weekend or public holiday data contained in the Stock Price Dataset. In order to avoid knowledge loss, the simple strategy of using the last weekday closing price resolved this. Missing data was also an issue on the Wikipedia dataset due to system failure on the host site recording the data. This was resolved through the use of the Holt Winters technique and appeared to reflect the pattern of data that existed in the dataset.

Optimal recommend derivation parameters were then used to obtain the Coppock values for each of the Stock Price datasets. These proved to facilitate the optimal correlations and did exceed most correlations that were derived when the monthly parameters were applied. Checks for correlation strength were then performed for each of the chose time frames over each of the years in question. These were then ranked in order of correlation strength and patterns relative to the characteristics of the stock market at the time were revealed.

Strengths and limitation were then highlighted with a view to understanding the process and to come up with recommended areas of future research.

6.4 Future work and research

Future work could concentrate on determining whether other techniques outside correlation checks can indicate a relationship between the Wikipedia article traffic statistic and the Coppock curve. One such technique is the Granger causality test. This was first proposed in 1969 by Clive Granger, which determines whether one time series is useful for forecasting the other (Baumohl and Vyrost 2010). Further research could also be performed in the area of event synchronisation, which measures synchronisation and time delay patterns between signals. One piece of work, completed by Quiriga et al. (2002), has investigated this in the area of brain waves between the left and right cortex of the brain. Their recommendation is to extend this research into other types of data. Therefore, Wikipedia article traffic statistics and the Coppock indicator could be suitable candidates for this. Finally, research performed by Kampf et al. (2014) using Wikipedia article statistics to determine relevance incorporating Wikipedia page view data for pages linked to the main (central) page of interest. Through this, including the local neighbourhood of pages linked to the central page of interest (node) may contribute to better correlations between this and the associated Coppock indicator, and thus could better confirm the signal provided by it.

APPENDIX A: ADDITIONAL MATERIAL

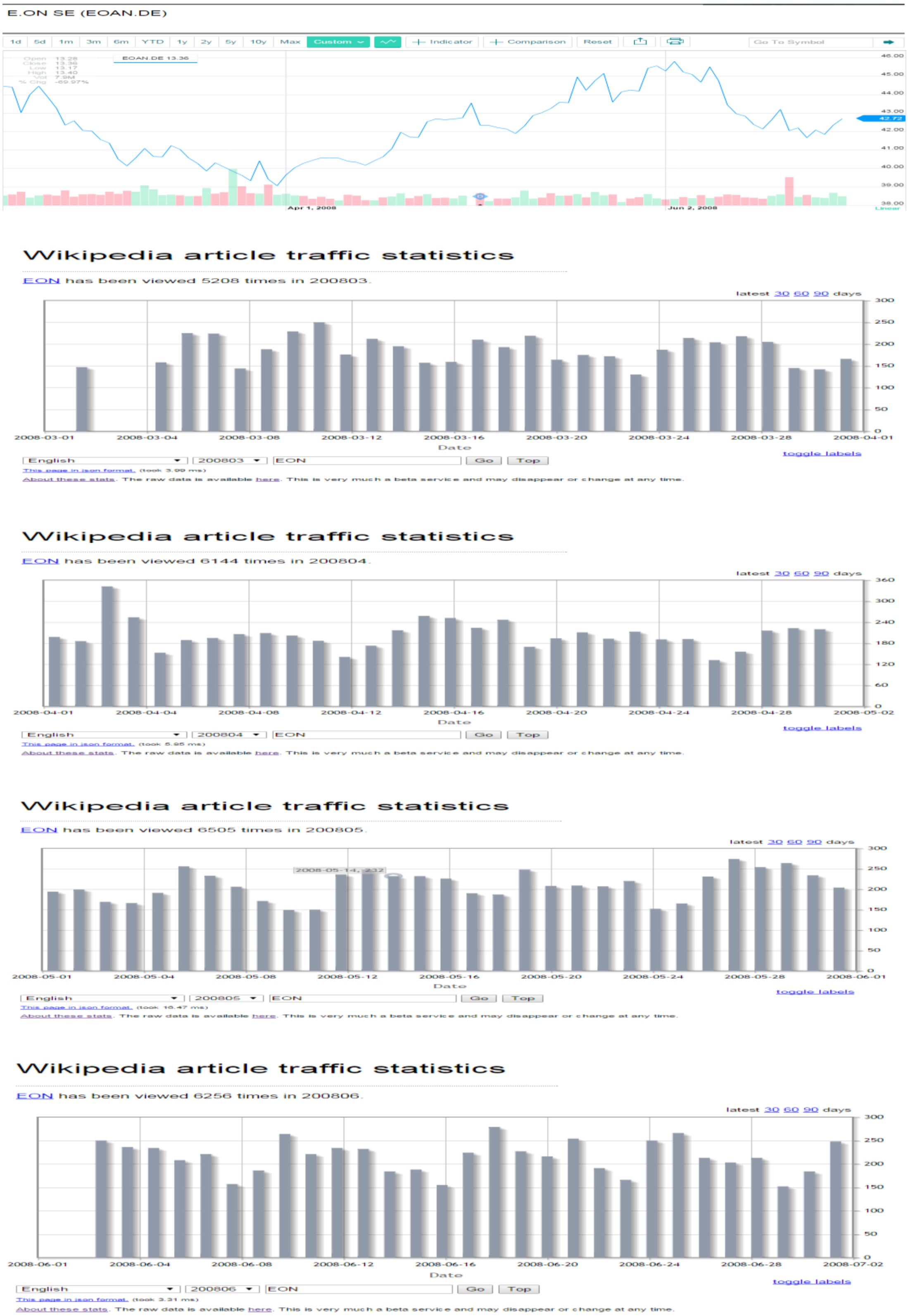

Figure 0.1: Sample of CSV Wikipedia Article Traffic Statistics for “Dow Jones” Page Views.

Date	WikiStats
01/03/2014	1394
02/03/2014	1547
03/03/2014	2937
04/03/2014	2809
05/03/2014	2813
06/03/2014	2659
07/03/2014	2837
08/03/2014	1550
09/03/2014	1468
10/03/2014	2528
11/03/2014	2703
12/03/2014	2837
13/03/2014	2715
14/03/2014	2672
15/03/2014	1364
16/03/2014	1453
17/03/2014	2362
18/03/2014	2610
19/03/2014	2347
20/03/2014	2666
21/03/2014	2392
22/03/2014	1389
23/03/2014	1442
24/03/2014	2392
25/03/2014	2683
26/03/2014	2916
27/03/2014	2629
28/03/2014	2236
29/03/2014	1377
30/03/2014	1382
31/03/2014	2426

Table 0.1: Sample of CSV Wikipedia Article Traffic Statistics for “Dow Jones” Page Views.

2008

3 month data set - January 2008 to March 2008 - Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.3778294484	0.0003822103	0.0000000398	0.0000000445	0.0157709688	0.007612353	0.115312827
BASF	0.1683041514	0.0002108233	0.0000120749	0.0000000000	0.0000000000	0.000000000	0.000000016
Bayer	0.0315005816	0.0000000909	0.0294069351	0.0002097663	0.0000020619	0.000002594	0.000109276
DAX	0.0176537500	0.0007076528	0.0000008457	0.0000008893	0.0000039573	0.000025737	0.000010806
DJIA	0.0128737754	0.0067951770	0.0000001588	0.0772825571	0.0003956415	0.001983539	0.002602739
EON	0.0039089922	0.0012009670	0.0000003399	0.0000000336	0.0000029724	0.000002331	0.000175539
Exxon Mobil	0.0029495136	0.3873591734	0.0001453240	0.0015550183	0.1061568921	0.055697205	0.075303217
General Electric	0.0028294650	0.0000032111	0.0000000020	0.0000938042	0.0000000254	0.000000049	0.000000018
Microsoft	0.0000323515	0.0091914089	0.0153581699	0.0000000111	0.0022226403	0.002336449	0.021097669
Procter & Gamble	0.0000000000	0.0002219606	0.0000000147	0.0000004988	0.0006199852	0.001757129	0.000532945
Siemens	0.0000000000	0.0005670832	0.0000074165	0.0002933750	0.0000599809	0.000851550	0.000250386
Walmart	0.0000000000	0.2560039531	0.0000000337	0.0342956796	0.2901326359	0.201320491	0.019194878

6 month data set - January to June 2008- Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.0000002903	0.3221712418	0.0000027651	0.0026837666	0.0000000023	0.000000003	0.000000028
BASF	0.0440687548	0.0017273337	0.0000019425	0.0000025473	0.0000000000	0.000000000	0.000000000
Bayer	0.0000000000	0.0000000027	0.0000149161	0.0014058483	0.0000002316	0.000000318	0.000001287
DAX	0.0000000000	0.0000004543	0.0000000000	0.0000000012	0.0000377821	0.000066303	0.000008289
DJIA	0.0000000000	0.0000423123	0.0000000000	0.0013913820	0.0003316629	0.016380262	0.000067474
EON	0.0000137806	0.2683176359	0.0000000039	0.0000000018	0.0000527872	0.000015360	0.014538752
Exxon Mobil	0.0012576369	0.8204082196	0.0000067138	0.0245034554	0.0013059669	0.001415245	0.015319670
General Electric	0.0000150906	0.0022373482	0.0000000000	0.0009104909	0.0000036714	0.000004649	0.000003038
Microsoft	0.0000000000	0.0000000253	0.0000000000	0.0000000000	0.0004917399	0.001105075	0.001605915
Procter & Gamble	0.0000421319	0.0000010137	0.0000000000	0.0000007514	0.0001802656	0.000168709	0.001077810
Siemens	0.0000000605	0.0000180747	0.0001571178	0.0000000042	0.0000012397	0.000008144	0.000000470
Walmart	0.0000300125	0.0004084994	0.0000866503	0.0000000119	0.0006584847	0.018937403	0.000086015

9 month data set - January to Sept 2008 - Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.0000000000	0.0000000002	0.0000000000	0.0000895912	0.0000000007	0.000000002	0.000000001
BASF	0.0066166055	0.0024594864	0.0012144895	0.0077284557	0.0000000006	0.000000000	0.000000159
Bayer	0.0000000000	0.0000000002	0.0000055555	0.0000002377	0.0000000002	0.000000001	0.000000002
DAX	0.0000000000	0.0000000541	0.0000000000	0.0000000376	0.0000034072	0.000005228	0.000000367
DJIA	0.0000000000	0.0000000000	0.0000000000	0.0000001820	0.0001934690	0.008517252	0.000002579
EON	0.0000040553	0.3015972699	0.0746222564	0.0000034302	0.0022978704	0.000518461	0.030536478
Exxon Mobil	0.0000029660	0.7009794124	0.0005025048	0.0002449383	0.0000560095	0.000029858	0.005572498
General Electric	0.0000250515	0.0123677831	0.0000000000	0.0000387828	0.0001652590	0.000039737	0.005378870
Microsoft	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0713752411	0.049064341	0.148877445
Procter & Gamble	0.0084609926	0.0001710225	0.0000000000	0.0000018412	0.0042478966	0.001829481	0.024644836
Siemens	0.0000000005	0.0000101490	0.0006371927	0.0000000000	0.0000027779	0.000004423	0.000007600
Walmart	0.0000000146	0.0005297058	0.0000000000	0.0000000001	0.0026997782	0.023418134	0.000359910

12 month data set - January to Dec 2008 - Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.0000000000	0.0000000001	0.0000000000	0.0000000000	0.0000000000	0.000000000	0.000000000
BASF	0.0000000264	0.0007493193	0.0009738359	0.0000000000	0.0000000001	0.000000000	0.000000000
Bayer	0.0000000000	0.0000000005	0.0000000508	0.0000000000	0.0000000000	0.000000000	0.000000000
DAX	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.000000000	0.000000000
DJIA	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.000000000	0.000000000
EON	0.0000000556	0.3067510321	0.0001006577	0.0000000000	0.0000000060	0.000000000	0.001518622
Exxon Mobil	0.0000007608	0.3198557459	0.0006771057	0.0000019908	0.0000374423	0.000033222	0.000053003
General Electric	0.0000765974	0.0151149929	0.0000000000	0.0000000000	0.0000000291	0.000000002	0.001099968
Microsoft	0.0000000000	0.0000000001	0.0000000000	0.0000000000	0.0001059455	0.000111619	0.020675292
Procter & Gamble	0.0026654069	0.0006843699	0.0000000000	0.0000175605	0.0000408233	0.000002362	0.010599647
Siemens	0.0000000000	0.0000010737	0.0047696227	0.0000000001	0.0000000917	0.000000357	0.000000001
Walmart	0.0000000000	0.0003740241	0.0000000000	0.0000000028	0.0000000000	0.000000000	0.000000000

Table 0.2: Shapiro-Wilk result on 2008 data (Wikipedia and Stock Price Data).

2014

3 month data set - January to March 2014 - Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.0052892808	0.0109488283	0.0000000208	0.0124164253	0.0063496485	0.015367962	0.000010188
BASF	0.0024183611	0.0000891160	0.0875397408	0.0010231245	0.0151801820	0.056170107	0.000086965
Bayer	0.0916864728	0.1131744736	0.0000275359	0.0185284328	0.0477389003	0.068589227	0.021798267
DAX	0.0015711668	0.0000276251	0.0000126364	0.0042459808	0.0059456354	0.012802696	0.000222202
DJIA	0.0002818130	0.0000054926	0.0000161544	0.0000020461	0.0021969066	0.002762484	0.000010241
EON	0.0154091381	0.0005224674	0.0000013271	0.1439487790	0.0087564828	0.000945042	0.166212245
Exxon Mobil	0.0500521166	0.0072810009	0.6033243308	0.0130647336	0.0460759701	0.059639810	0.001638622
General Electric	0.0010909351	0.0000045732	0.0081882909	0.0013310870	0.0020181426	0.027417073	0.000075303
Microsoft	0.0000000000	0.0000000126	0.0000354096	0.0002543409	0.0205648681	0.036694745	0.193754408
Procter & Gamble	0.0000000000	0.0000000000	0.0000109552	0.0218015689	0.2431819652	0.197085582	0.000221682
Siemens	0.0000069750	0.0000000000	0.0000017602	0.1942534563	0.0709317625	0.032003560	0.113336299
Walmart	0.0011290679	0.0000380959	0.0000006897	0.0072131921	0.0001866043	0.002308619	0.000011122

6 month data set - January to June 2014 - Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.0000134320	0.0000128745	0.0000000000	0.0003548352	0.0000528975	0.000223390	0.000000514
BASF	0.0000000079	0.0000008285	0.0000117727	0.0000000584	0.0000186901	0.000188019	0.000000149
Bayer	0.0000006013	0.0026466055	0.0000000000	0.0047199829	0.0008241028	0.003309919	0.000217225
DAX	0.0000275828	0.0000000268	0.0000000000	0.0043443183	0.0002245844	0.001361665	0.000023354
DJIA	0.0001148380	0.0000003317	0.0000033458	0.0001666523	0.0000000617	0.000000039	0.000000001
EON	0.0000001730	0.0000130480	0.0000000003	0.0000000002	0.1149247364	0.107473656	0.011789304
Exxon Mobil	0.1419507426	0.0109295334	0.0002067621	0.0000060425	0.0000138000	0.000065872	0.000000025
General Electric	0.0080485700	0.0008345007	0.0025442812	0.0000293435	0.0000001968	0.000006382	0.000000000
Microsoft	0.0000000000	0.0000000024	0.0000000000	0.0000063177	0.0002307607	0.000731776	0.156128674
Procter & Gamble	0.0000000000	0.0000000000	0.0000000000	0.3890293588	0.0041644408	0.142907779	0.000016142
Siemens	0.0000000229	0.0000000000	0.0000000047	0.0206008351	0.0632932530	0.023802329	0.028575748
Walmart	0.0038670439	0.0000432804	0.0000000119	0.0156708765	0.0000005852	0.000012471	0.000000247

9 month data set - January to Sept 2014 - Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.0000000000	0.0000000132	0.0000000000	0.0002436771	0.0000000349	0.000000068	0.000000001
BASF	0.0000000001	0.0000000107	0.0000001806	0.0000000013	0.0000013902	0.000006116	0.000000018
Bayer	0.0000000014	0.0014747667	0.0000000000	0.0003567399	0.0000027088	0.000046140	0.000001030
DAX	0.0000000000	0.0000000001	0.0000000000	0.0010805729	0.0000524202	0.000157992	0.000008361
DJIA	0.0001037798	0.0000005430	0.0000076358	0.0000027942	0.0000000009	0.000000001	0.000000000
EON	0.0000000074	0.0000001975	0.0000000000	0.0000000121	0.0000031939	0.000004207	0.000031061
Exxon Mobil	0.0001333419	0.1086410789	0.0000000003	0.0000001935	0.0006260513	0.001194507	0.000021463
General Electric	0.0000092930	0.0044847296	0.0000149265	0.0001261419	0.0000000277	0.000000861	0.000000000
Microsoft	0.0000000000	0.0000000000	0.0000000000	0.0000009159	0.0007832260	0.001015913	0.203615357
Procter & Gamble	0.0000000000	0.0000000000	0.0000000000	0.0000410575	0.0256954398	0.162823727	0.000833405
Siemens	0.0000000364	0.0000000000	0.0000000000	0.0000587189	0.0011121392	0.001931014	0.000020166
Walmart	0.0000000534	0.0002401638	0.0000000094	0.0010958380	0.0000000003	0.000000006	0.000000001

12 month data set - January to Dec 2014 - Shapiro-Wilk Results

Company	Raw Wiki	Log10 Wiki	SROC Wiki	Raw Price	Coppock (14-11-10)	Coppock (14-11-6)	Coppock (20-10-10)
Allianz	0.0000000000	0.0000000029	0.0000000000	0.0000000192	0.0000000003	0.000000001	0.000000001
BASF	0.0000000000	0.0000000002	0.0000000006	0.0000054112	0.0000000166	0.000000142	0.000000000
Bayer	0.0000000021	0.0000426740	0.0000000000	0.0000000002	0.0000088084	0.000050203	0.000003614
DAX	0.0000000000	0.0000000000	0.0000000000	0.0000060370	0.0000846789	0.000083679	0.000067125
DJIA	0.0000023930	0.0000000105	0.0000117245	0.0000014346	0.0000008711	0.000000319	0.000000072
EON	0.0000000000	0.0000000085	0.0000000000	0.0000000041	0.0000337667	0.000043278	0.000029450
Exxon Mobil	0.0000000000	0.0000007604	0.0000000043	0.0000174835	0.1861103871	0.328121857	0.000009086
General Electric	0.0003697816	0.0000000002	0.0003512360	0.0000585363	0.0000114743	0.000347651	0.000000003
Microsoft	0.0000000000	0.0000000000	0.0000000000	0.0000000013	0.0008599120	0.001751839	0.061140607
Procter & Gamble	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0010609758	0.000942969	0.000838361
Siemens	0.0000000006	0.0000000000	0.0000000000	0.0000000000	0.0049676239	0.008268280	0.000010995
Walmart	0.0000110523	0.0030332791	0.0000000001	0.0000000000	0.0000000004	0.000000007	0.000000000

Table 0.3: Shapiro-Wilk result on 2014 data (Wikipedia and Stock Price Data).

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